Identifying hot spots of cardiometabolic risk factors in a Swiss city: impact of individual and environmental factors

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Research Article

Keywords: cardiometabolic risk factors, spatial relative risk, geographically weighted regression, social and physical environments

Posted Date: September 25th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-3359714/v1

Abstract

Background:

Cardiovascular disease (CVD) remains a major public health concern, and developing effective interventions at the population level requires a thorough understanding of the spatial distribution and contextual determinants of cardiometabolic risk factors (CMRFs). However, knowledge on these issues at small spatial scales is still limited, especially in Europe. The aim of this study was to explore the spatial patterns of CMRFs and to identify key individual and contextual factors associated with these risk factors in the city of Lausanne, Switzerland.

Methods:

Using individual-level data from a population-based cohort of middle-aged and older adults (CoLaus), we examined hypertension, obesity, diabetes, and dyslipidemia as key CMRFs. Intensity functions were used to identify areas of elevated risk for each outcome. Geographically weighted regressions were then employed to examine local associations between outcomes adjusted for individual confounders, and characteristics of physical and social environments such as air pollution, noise, greenness, street connectivity, socioeconomic position, and ethnic composition.

Results:

We analyzed data from 3,695 participants (mean age of 64.1 years, 56.8% females). The prevalence of hypertension was 48.2%, obesity 17.7%, diabetes 10.7% and dyslipidemia 33.2%. Among the individual factors associated with CMRFs, older age, male sex, lower education level, and being foreign-born emerged as common contributors. Persistent spatial clusters for hypertension, obesity, and diabetes were identified across the city, as well as areas with concurrent increased risk for multiple CMRFs. After adjustment for individual confounders, a global association between neighborhood income and hypertension, obesity, and diabetes emerged. Obesity showed the strongest contextual influence, with significant local associations identified between obesity and higher unemployment rates, lower income, education, and greenness. Notably, hypertension showed local associations with lower neighborhood income and PM2.5 concentrations, while diabetes was associated with lower income and higher unemployment. Dyslipidemia did not show significant associations with contextual factors.

Conclusions:

Using individual-level data, the study combined spatial approaches to delineate high-risk areas for CMRFs within an urban area and to reveal significant associations with characteristics of physical and social environments. This methodological framework can be applied elsewhere, providing public health practitioners with essential insights to prioritize and tailor local population-level initiatives for CVD prevention.

Background

Cardiovascular disease (CVD) is a major cause of death and disability in European countries, and there is growing concern about its increasing prevalence in the future (1). The COVID-19 pandemic has further exacerbated the challenges faced by individuals with CVD. Not only do they face an increased risk of severe COVID-19, but they also experience collateral damage from pandemic response measures, including poor management of behavioral risk factors for noncommunicable disease during lockdown and disruptions in access to routine health services (1–3).

Geographic variations in the prevalence of the most common CVD risk factors, such as diabetes, obesity, hypertension, and dyslipidemia (collectively referred to as cardiometabolic risk factors or CMRFs), have been observed at different spatial scales, and these variations have been associated with characteristics of the social and physical environment (4–6). While obesity has been extensively studied compared to hypertension, diabetes, and dyslipidemia, all CMRFs consistently showed associations with the social environment, with higher risks found in low socioeconomic neighborhoods (7). Obesity has also been associated with low neighborhood walkability, low greenness, and physical deterioration of the neighborhood (8, 9).

Hypertension has been associated with traffic noise, air pollution, low walkability, and low greenness (10–13). Diabetes has been shown to be associated with road traffic noise, air pollution, low walkability, and low access to green spaces (9, 13–15). Dyslipidemia has been associated with low greenness and higher urbanization (11, 16).

These associations between CMRFs and contextual factors may explain the limited effectiveness of individual-centered prevention strategies, which often fail to address environmental and societal barriers to healthy lifestyles (7, 17). In contrast, population-level interventions, which have been advocated for decades (18), focus on modifying the environment to promote lifestyle behaviors and minimize risk factors for the entire population (19). The integration of both individual- and population-based strategies is therefore crucial to effectively reduce the overall prevalence of CVD and address health inequities (18–20).

Developing population-level interventions requires two key components: identifying high-risk areas to prioritize interventions and understanding the specific characteristics of the social and physical environment on which to focus prevention efforts. However, achieving this at the local level can be challenging due to the limited availability of fine-scale health data, which are typically only available at the national or regional level (4, 6). Furthermore, generalizing findings on health-environment associations is hampered by the heterogeneity of methods and indicators used, as well as by inherent contextual differences between regions and countries (21, 22).

Therefore, the aim of this study is to perform a spatial analysis using individual-level data from a large population-based cohort in Lausanne, Switzerland. The study aims to (1) assess the intra-urban spatial variation in cardiometabolic risk factors, (2) investigate the characteristics of the social and physical environment that may explain these variations while controlling for individual confounders, and (3) discuss the implications of these findings for the development of population-level interventions to address CMRFs.

Materials and methods

Data

Study population

Data were obtained from the CoLaus-PsyColaus population-based study (23), which aims to assess the prevalence and identify the genetic, biological, and environmental determinants of CVD in the city of Lausanne, Switzerland (41 km^2 and 140,202 inhabitants in 2021 (24)). Participants were chosen to be representative of the population aged 35–75 years, following the selection procedure described in Firmann et al. (23). The study was approved by the Institutional Ethics Committee of the University of Lausanne and complies with the 1964 Helsinki declaration. All participants provided written informed consent.

A baseline recruitment phase took place between 2003 and 2006 (N = 6733) and was followed by three follow-up studies carried out from 2009 to 2012 (N = 5064), 2014 to 2017 (N = 4881), and 2018 to 2021 (N = 3751). In this study, we used the data from the second follow-up period (2014–2017) as the last follow-up was highly perturbed by the COVID-19 pandemic.

Health outcomes

The presence of cardiometabolic conditions (diabetes, hypertension, obesity, and dyslipidemia) was assessed by medical examination. Diabetes was defined as a fasting blood glucose level of ≥ 7 mmol/L and/or the use of antidiabetic treatment (25). Hypertension was identified as a systolic blood pressure > 140 mmHg or a diastolic blood pressure 90 mmHg and/or the use of antihypertensive drug treatment. Obesity was defined as a body mass index (BMI) ≥ 30 kg/m^2, according to World Health Organization guidelines (26). Dyslipidemia was determined by a total cholesterol level > 6.5 mmol/L and/or an LDL-cholesterol level > 4.1 mmol/L, and/or the use of hypolipidemic medication (27).

Individual factors

Demographic (age, sex, marital status, country of birth), socioeconomic (education, poverty), and behavioral risk factors (smoking status, alcohol consumption, physical inactivity) were assessed using validated questionnaires administered to the study participants. Home addresses provided by the participants at the time of the examination were geocoded by matching with the official Swiss address directory (28).

Marital status was classified as married/cohabiting or living alone. Country of birth was categorized as "born in Switzerland" or "not born in Switzerland". Education level was divided into low (obligatory school or apprenticeship), medium (high school), or high (university degree). Poverty was considered for individuals who answered positively to “Are you experiencing real financial difficulties to meet needs?”. Smoking status was classified as current or former/never smoker. Hazardous drinking was considered for participants consuming over 14 units per week (one unit = one glass of wine, one can of beer or one shot of spirit). Physical inactivity was defined as having a sedentary lifestyle.

Contextual variables

To comprehensively assess the influence of the residential environment on CMRFs, we considered several indicators of the social and physical environments that have previously been associated with diabetes, hypertension, obesity, or dyslipidemia. Our analysis included measures of urban walkability, environmental exposures, material deprivation, and ethnic composition.

Two key measures were used to reflect urban walkability: greenness and street connectivity. Greenness was determined by calculating the proportion of green space within a 500-meter radius buffer around each hectare centroid using land cover data for the year 2015 (Source: Géodonnées Etat de Vaud). The choice of a 500-meter buffer was justified by its common use in assessing walkability in European urban areas (12, 29), corresponding to places accessible within a 5–10-minute walk. For street connectivity, we calculated intersection density by counting the number of intersections with three or more legs within the 500-meter buffer. The walkable street network from January 2016 was retrieved from OpenStreetMap using the Overpass API, excluding private roads and nonrelevant intersections (parking aisles, service driveways, etc.).

Nighttime traffic noise exposure was obtained from the 2015 sonBASE dataset (10x10 m resolution) (30), and the concentrations of $PM_{2.5}$ and NO_2 were extracted from the 2015 Pollumap immission model developed by MeteoTest (20x20 m resolution) (31). We then calculated the mean exposure in noise (dB) and air pollutants (in $\mu g/m^3$) in the 500-meter buffers around hectare centroids.

To reflect the material deprivation and ethnic composition of the neighborhood, we considered indicators reflecting the proportion of the population with compulsory education, median neighborhood income, unemployment rate, and proportion of non-Swiss citizenship (i.e., foreign population). Data for these indicators were obtained from MICROGIS for the Swiss neighborhoods in 2015 (32).

All contextual variables were computed using Python and QGIS at the resolution of inhabited hectares (100x100 m cells), which is the scale used by the Swiss Federal Statistical Office for population statistics (33). The assignment of contextual factors to CoLaus participants was achieved by spatial intersection.

Methods

Spatial relative risk of cardiometabolic risk factors

To assess the spatial variation in CMRFs across the study area, we compared the spatial density estimations between cases (i.e., individuals with the disease) and controls (i.e., non-cases) by modeling the individual’s home locations as point patterns following a heterogeneous Poisson distribution (34, 35). Random perturbations and edge correction techniques were applied to address potential issues with duplicate point locations and boundary effects (36).

The log relative risk surface, obtained by taking the ratio of the density functions of cases and controls, allowed the identification of high-risk and low-risk areas, indicating areas with significantly elevated or reduced probabilities of observing a case, respectively (35). We also assessed the overall clustering of CMRFs across the study area using the method proposed by Kelsall and Diggle (37).

The choice of the kernel form and, more importantly, the kernel bandwidth play a critical role in the estimation of spatial relative risk as it determines the degree of smoothing applied to the risk surface (see Supplementary Fig. 1, Additional File 1 for bandwidth comparisons). A larger bandwidth could mask small-scale patterns and reduce local variations, whereas a bandwidth that is too small could introduce noise and overfitting. For this study, we chose a circular Gaussian kernel with a bandwidth of 200 m, which was a compromise between the jointly optimal bandwidths proposed by Kelsall and Diggle (38) and Davies (39).

Statistical inference of the relative risk surface involved testing the random labeling hypothesis through 999 Monte Carlo permutations. In each permutation, the set of events (cases and controls) was randomly assigned to point locations. Tolerance contours were then derived from the resulting p-value surface, defining high-risk and low-risk areas at significance levels of 5% and 1%.

To ensure the robustness of the findings, the spatial patterns of CMRFs observed in the study sample (i.e., second follow-up of the CoLaus study) were compared with those observed at baseline and at the first follow-up. It aimed to address concerns about the representativeness of the cohort and identify consistent high-risk areas over a 10-year period.

As an initial exploration prior to the modeling phase, we analyzed differences in participant characteristics and contextual factors between areas with significantly elevated risk, reduced risk, or a neutral risk pattern (where the observed variation is not statistically significant) of CMRFs. Pairwise comparisons of study participants and inhabited hectares located in high-risk, low-risk, and neutral areas were performed using chi-square and Kruskal-Wallis tests for categorical and continuous variables, respectively. A Bonferroni correction was applied to p-values to account for multiple comparisons.

Analyses were performed in R using the *sparr* (40) and *smacpod* (41) packages.

Regression models

To investigate the associations between CMRFs (hypertension, diabetes, obesity, and dyslipidemia) and the physical and social environments, we used several regression models. Our aim was to disentangle the effects of contextual factors and known individual confounders while exploring the spatially varying relationships between CMRFs and the environment.

As the spatial variation in disease risk could be misattributed to contextual factors rather than differences in individual characteristics acting as confounders (7), we initially adjusted our binary health outcomes using logistic regression models. These models accounted for important individual confounders, including age, sex, poverty status (yes vs. no), education level (low, medium, high), and country of birth (Swiss-born vs. foreign-born). By considering the Pearson residuals of these logistic regression models, we obtained adjusted health outcomes that captured the proportion of the health outcome not explained by the individual factors (42). These adjusted health outcomes were then used to assess the associations with contextual factors. In addition, to account for the nonlinear relationships between age and conditions like diabetes, obesity, and dyslipidemia, we incorporated quadratic terms for these outcomes into the regression models.

Standard regression models, such as ordinary least squares (OLS), face challenges in examining health-environment relationships due to the inherent spatial clustering and potential spatial heterogeneity of geographic data. Spatial clustering refers to the tendency for nearby locations to exhibit similar values, violating the assumption of independence in OLS. On the other hand, spatial heterogeneity implies that the relationship between an outcome and its explanatory variables may vary across space, rendering global models inadequate. To address these issues, we used geographically weighted regression (GWR) models (43). GWR determines model parameters at each regression point, based on nearby data points. The influence of each data point is weighted by its distance from the regression point, typically using a bisquare kernel. In contrast, OLS weights all points in the study area equally.

Our analysis proceeded in two stages. First, we conducted an OLS analysis to gain insight into the overall associations between the adjusted CMRFs and the contextual factors described above, including street connectivity, greenness, traffic noise, $PM_{2.5}$ and NO_2 exposure, median income, unemployment rate, proportion of compulsory education, and proportion of foreign population. The OLS analysis provided an opportunity to identify potential multicollinearity issues using the variance inflation factor (VIF) and to assess the spatial autocorrelation of the residuals using the global Moran's I index. For the latter, we used a Gaussian kernel bandwidth of 200 meters, consistent with the bandwidth employed for kernel density estimation.

We then built GWR models to explore the spatially varying relationships between the adjusted CMRFs and the contextual factors with VIF < 10. The selection of the kernel bandwidth (i.e., the number of nearby points considered in the regression calculations) involved a golden search method that minimizes the corrected Akaike Information Criterion (AICc) (44). To account for variations in point density, we chose a bisquare adaptive kernel. While GWR used the same kernel bandwidth for each process included in the model (i.e., each explanatory variable), we also considered the multiscale extension (MGWR), which recognizes that spatial processes may vary at different scales and determines a unique bandwidth for each explanatory variable. The GWR and MGWR models provided coefficient estimates, t-values, and local model diagnostics for each regression point, allowing us to identify statistically significant health-environment associations using t-values adjusted for multiple comparisons (45).

To visualize the results of the GWR and MGWR models, we mapped the coefficient estimates for each contextual variable, and the locations where the associations were statistically significant. We used the AICc criterion to compare spatial models, with a reduction in AICc values > 2 was considered indicative of substantial improvement (29).

The regression modeling steps were performed using R (46) and the *mgwr* (44) and *PySAL* (47) libraries in Python.

Results

Out of the 4,881 participants included in the study during the second follow-up period (2014–2017), 61 individuals (1.25%) could not be geocoded, and 1,117 individuals (22.88%) were excluded because they resided outside the urban districts of Lausanne. Additional exclusions comprised participants with missing individual confounder data (N = 4, 0.08%) and those with missing neighborhood characteristics (N = 4, 0.08%). Thus, 3,695 participants (75.70%) were included in the final analysis (Supplementary Fig. 2C, Additional File 1).

The mean age of the participants was 64.1 ± 10.5 years, and 56.8% were females. The prevalence of CMRFs in the study sample was as follows: 48.2% were hypertensive, 17.7% were obese, 10.7% had diabetes, and 33.2% had dyslipidemia. Detailed information on outcome variables and participant characteristics, including demographic, socioeconomic, and behavioral factors, is presented in Supplementary Tables 1 and 2, Additional File 2. Supplementary Table 1 also provides comparative statistics between the study sample, the baseline population, and the population excluded from the study.

Regarding the characteristics of the physical and social environments, all variables displayed spatial variation across the city (see Supplementary Fig. 3, Additional File 1). Within a 500-meter radius buffer, the mean values of environmental factors were as follows: intersection density was 1.0e-4 (std: 5.0e-5), proportion of green spaces was 52.2% (std: 18.1), nighttime traffic noise was 41.6 dB (std: 3.67), $PM_{2.5}$ concentration was 10.5 μg/m^3 (std: 0.32), and NO_2 concentration was 22.4 μg/m^3 (std: 2.07). Additionally, the average median income per inhabited hectare was 41.2 kCHF/year (std: 19.2), (1 CHF = 1.04 € or 1.14 US$ as of 31st July 2023) the unemployment rate was 3.97% (std: 2.64), the proportion of the population with compulsory education was 20.2% (std: 12.2), and the proportion of the foreign population was 40.5% (std: 17.2).

Intra-urban variation in cardiometabolic risk

Log relative risk surfaces of CMRFs are shown in Fig. 1, along with the delineation of areas of significantly elevated risk at the 5% (dashed line) and 1% (solid line) significance levels. The delineation of high-risk, low-risk and neutral-risk areas is shown in Supplementary Fig. 4, Additional File 1.

Hypertension

Hypertension exhibited spatial variation across the city, with four large areas exceeding the 95% tolerance interval, in landmarks #2, #3, #4, and #7 (Fig. 1A). The test for global clustering was also significant, with a p-value of 0.04. High-risk areas were characterized by lower income and education levels than low-risk and neutral areas (Supplementary Fig. 5, Additional File 1). We also observed lower street connectivity and, surprisingly, higher greenness and lower environmental exposure (nighttime noise and air pollution) compared to low-risk areas, but the difference was not statistically significant compared to neutral areas. Study participants in high-risk areas were older ($p = 0.005$), had lower levels of education ($p < 0.001$), and were more likely to be foreigners ($p = 0.013$) and unemployed ($p = 0.029$).

Obesity

Obesity showed a global clustering pattern ($p = 0.03$), and we identified five local clusters exceeding the 99% tolerance interval (Fig. 1B), in landmarks #1, #2, #5, #6, and #8. High-risk areas were associated with higher socioeconomic deprivation and a higher proportion of foreign population than low-risk and neutral areas (Supplementary Fig. 6, Additional File 1). While there were no significant variations in walkability, high-risk areas had statistically higher environmental exposures (nighttime noise and air pollution). In addition, study participants in high-risk areas were younger ($p < 0.001$) and more likely to be foreigners ($p < 0.001$), to live alone ($p = 0.002$), to have a low level of education ($p < 0.001$), and to experience financial difficulties ($p < 0.001$).

Diabetes

Diabetes demonstrated spatial variation across the study area, with two local clusters detected at a significance level of 1% in landmarks #2 and #6 (Fig. 1C). There was no evidence of global clustering ($p = 0.61$). High-risk areas had lower walkability and higher environmental exposures compared to low-risk and neutral areas (Supplementary Fig. 7, Additional File 1). Inhabited hectares in high-risk areas were also characterized by a lower median income, a higher proportion of the population with compulsory education, and a higher proportion of foreign population. Study participants in high-risk areas were more likely to have lower levels of education ($p < 0.001$), higher unemployment rates ($p = 0.020$), and higher financial difficulties ($p = 0.004$).

Dyslipidemia

Dyslipidemia exhibited a less pronounced spatial pattern than the other CMRFs, but one local cluster in the northeastern part of the city (landmark #5) was significant at the 1% significance level (Fig. 1D). There was no evidence of global clustering ($p = 0.37$). High-risk areas were characterized by lower median income, higher unemployment rate, and higher nighttime traffic noise and NO_2 exposure compared to other risk areas (Supplementary Fig. 8, Additional File 1). No significant differences were observed between study participants, except for education level ($p < 0.001$).

The spatial pattern of CMRFs was generally consistent with the patterns observed at baseline and the first follow-up study period (Supplementary Figs. 9–12, Additional File 1), highlighting the long-term persistence of high-risk areas despite individuals leaving the cohort.

Impact of individual confounders on cardiometabolic risk factors

Results of multivariate logistic regressions, adjusting CMRFs for individual confounders, are presented in Supplementary Table 3, Additional File 2. Together, age, sex, poverty, education, and country of birth explained 11%, 4%, 12%, and 6% of the variation in hypertension, obesity, diabetes, and dyslipidemia, respectively. Males were more likely than females to have hypertension, obesity, diabetes, and dyslipidemia. Individuals with lower education levels, older age, and those born outside Switzerland were also at higher risk for these CMRFs. Although individuals with financial difficulties had an increased risk of hypertension, obesity, and diabetes, the association with dyslipidemia was not statistically significant.

Associations with the physical and social environments

The results of the global regression model are presented in Table 1. After adjustment for individual confounders, only median neighborhood income was negatively associated with hypertension, obesity, and diabetes. However, no significant global associations were found between adjusted dyslipidemia and characteristics of the physical and social environments. VIF values were all below the common threshold of 10 for each CMRF, so all the explanatory variables were included in the spatial regression models. Notably, Global Moran's I suggested a positive spatial autocorrelation of the residuals, indicating that the OLS model may not be suitable for effectively modeling the relationships between adjusted CMRFs and contextual factors.

Table 1

Results of the ordinary least squares (OLS) regression model. Health outcomes were previously adjusted for individual confounders, including age, sex, education, income, and country of birth, using a logistic regression model (see Supplementary Table 3, Additional File 2 for details). n/a: not available, I: Global Moran's I of residuals, p: p-value, Coeff.: Coefficient estimates, VIF: Variance Inflation Factor.

	Hypertension			**Obesity**			**Diabetes**			**Dyslipidemia**		
	N = 3569			**N = 3411**			**N = 3460**			**N = 3405**		
	I = 0.033 (p = 0)			I = 0.041 (p = 0)			I = 0.031 (p = 0)			I = 0.026 (p = 0)		
Variable	**Coeff.**	**p**	**VIF**	**Coeff.**	**p**	**VIF**	**Coeff.**	**p**	**VIF**	**Coeff.**	**p**	**VIF**
Intercept	0.000	0.984	n/a	0.000	1.000	n/a	-0.002	0.926	n/a	-0.001	0.945	n/a
Street connectivity	0.042	0.276	5.34	-0.023	0.567	5.29	-0.031	0.426	5.310	-0.011	0.779	5.26
Greenness	0.001	0.984	4.52	-0.018	0.612	4.48	-0.042	0.239	4.490	-0.023	0.527	4.44
Nighttime noise	0.005	0.848	2.72	-0.013	0.653	2.73	0.024	0.390	2.720	0.016	0.569	2.72
$PM_{2.5}$	-0.076	0.148	9.71	0.012	0.820	9.76	0.009	0.868	9.710	0.008	0.880	9.60
NO_2	-0.018	0.622	4.86	0.000	0.995	4.89	-0.053	0.149	4.840	-0.027	0.475	4.82
Median income	**-0.061**	0.002	1.35	**-0.046**	0.019	1.35	**-0.044**	0.023	1.340	-0.008	0.694	1.34
Unemployment rate	0.025	0.208	1.41	0.031	0.120	1.40	0.018	0.375	1.400	-0.003	0.899	1.40
Compulsory education	0.010	0.648	1.61	0.011	0.616	1.60	0.014	0.517	1.610	-0.003	-0.142	1.61
Foreign population	0.004	0.846	1.41	0.006	0.763	1.41	0.037	0.062	1.410	0.012	0.578	1.40

Hypertension

The MGWR model demonstrated superior performance in capturing the relationships between adjusted hypertension and contextual factors, as evidenced by its lower AIC (10,135) compared with the OLS (AIC = 10,139) and GWR (AIC = 10,141) models (Supplementary Table 4, Additional File 2). In both spatial models, the local condition numbers remained below 15, indicating no multicollinearity issues (Supplementary Fig. 13, Additional File 1). The bandwidths used in the MGWR model were similar to those used in the GWR model, except for $PM_{2.5}$ exposure (1137 neighbors for MGWR bandwidth vs. 3568 for GWR, Supplementary Table 5, Additional File 2). Contextual factors that significantly explained the spatial variation in adjusted hypertension are shown in Fig. 2 for the MGWR model and in Supplementary Fig. 13, Additional File 1 for GWR. Neighborhood median income displayed a small negative association with hypertension, and this association was statistically significant throughout the city except in the southeastern region. In addition, we observed a negative local association between $PM_{2.5}$ exposure and adjusted hypertension, which was significant only in the MGWR model and overlapped the high-risk areas in landmarks #3 and #4.

Obesity

The MGWR model (AICc = 9649) outperformed both the OLS (AIC = 9676) and GWR (AIC = 9654) models (Supplementary Table 4, Additional File 2). The map of local condition numbers (Supplementary Fig. 16, Additional File 1) indicated that certain locations in the GWR model exceeded the common threshold of 30, suggesting potential multicollinearity problems in these areas. In addition, the different bandwidths used in the MGWR model (ranging from 1010 to 3409 neighbors, Supplementary Table 5, Additional File 2) suggested different process scales among the contextual factors.

The left panels of Fig. 3 illustrate the spatial variation in the MGWR coefficient estimates. Neighborhood income and unemployment rate showed respectively negative and positive associations with obesity risk across the city, albeit with modest effects (coefficient estimates between − 0.1 and 0.1). These spatial associations were regionally significant (right panels of Fig. 3) and overlapped with high-risk areas identified in the log relative risk surface, specifically in landmarks #1, #2, #3, and #5 for median income, and #1, #2, #6, and #8 for unemployment. Both greenness and the proportion of compulsory education showed spatial heterogeneity across the city, with their associations changing sign depending on the area. In the south, a moderate local negative association between greenness and obesity risk was observed, partially overlapping with the high-risk area located in landmark #2. The proportion of compulsory education was positively associated with obesity risk in the eastern high-risk area (landmark #1).

In contrast to the MGWR model, the GWR model (Supplementary Fig. 14, Additional File 1) did not reveal a significant association between education level and adjusted obesity but showed a significant positive association with greenness in the northern areas (landmark #5) and a negative association with street connectivity in landmark #1.

Diabetes

For adjusted diabetes, a modest increase was observed in the proportion of explained variance between the global and spatial models (GWR and MGWR), but model fit did not show improvement (Supplementary Table 4, Additional File 2). The MGWR model (AICc = 9743) slightly outperformed the GWR model (AICc = 9745). Local multicollinearity was low across the study area (Supplementary Fig. 16, Additional File 1), and all explanatory variables operated at the global scale except for median income (659 neighbors for MGWR bandwidth vs. 3458 for GWR). Significant contextual associations with diabetes were exclusively related to social characteristics (Fig. 4, Supplementary Fig. 15, Additional File 1). Both spatial models showed significant negative associations between neighborhood income and obesity in the northern areas. However, the coefficient estimate surface showed moderate spatially heterogeneous associations in the MGWR model and small negative associations in the GWR model, which can be explained by the different process scales considered in the two models. The proportion of the foreign population showed a slight negative association in both GWR and MGWR, with locally significant associations in the south of the city (landmark #8).

Dyslipidemia

As suggested by the global regression model, the GWR and MGWR models corroborated the negligible effect of the physical and social environments on adjusted dyslipidemia across our study area. This was highlighted by the lack of improvement in model performance and the absence of significant local associations for all contextual factors (Supplementary Table 4, Additional File 2 and Fig. 20, Additional File 1).

Discussion

Our study aimed to investigate the spatial variation in cardiometabolic risk factors (CMRFs) in an urban context and to explore the role of the physical and social environments in shaping these patterns while considering individual confounders. The results revealed significant spatial patterns in CMRFs as well as several local associations with the environment, providing valuable insights to support local interventions and improve the living environment of affected populations.

Intra-urban variation in cardiometabolic risk factors

We observed substantial spatial variation in CMRFs across Lausanne, with obesity exhibiting the most pronounced pattern, followed by hypertension and diabetes. The log relative risk of these cardiometabolic outcomes exceeded the 99% tolerance interval in several areas, and we also observed a global clustering pattern for obesity and hypertension. In particular, our investigation revealed a higher risk of obesity in the western areas of the city (landmarks #1, #2, #3). This finding is consistent with previous research by Joost et al. (48), who reported a striking westward gradient in BMI for the baseline and first follow-up of the same medical cohort, although the magnitude of the gradient was somewhat attenuated in our study.

Furthermore, our study identified overlapping high-risk areas associated with multiple cardiometabolic risk factors. Specifically, the neighborhood in landmark #2 had a concurrent elevated risk for obesity and diabetes, whereas the neighborhood in landmark #5 had an elevated risk for obesity and dyslipidemia. These findings suggest that targeted interventions should be prioritized in these areas, as they may indicate a higher risk of multimorbidity.

Associations with the physical and social environments

The associations between cardiometabolic risk factors and characteristics of the physical and social environments were examined using geographically weighted regressions (GWR) on health outcomes previously adjusted for known individual confounders, including age, sex, education, country of birth, and poverty.

For obesity, our analysis revealed significant local positive associations with unemployment rate and compulsory education, and negative associations with neighborhood income, even after controlling for individual socioeconomic status. These findings are in line with the literature, which consistently highlights the association between weight status and neighborhood socioeconomic position (7). We also observed a significant negative local association between obesity and greenness in the southern areas, consistent with other studies (8, 49).

Hypertension displayed a negative global association with neighborhood income, which was significant in the eastern and northern areas in our spatial models. This association between hypertension and socioeconomic deprivation is consistent with findings from other studies (50, 51). However, it is interesting to note that while several variables were included in our study to characterize the socioeconomic position of the neighborhood, only neighborhood income emerged as a significant negative association with hypertension. This differs from the study by Chaix et al. (52), where neighborhood education, not income, was identified as a significant factor. Surprisingly, we also found a local negative association between the concentration of $PM_{2.5}$ and adjusted hypertension, which might suggest potential mediating interactions with another environmental characteristic. It is worth noting that the neighborhoods in question (landmarks #3 and #4) are situated next to a small civil airport, and our variable for nighttime traffic noise did not include aircraft sources. This could provide a clue for further investigations, as associations between aircraft noise exposure and hypertension have been observed in other studies (53, 54).

Our study did not detect any local association between diabetes and the characteristics of the physical environment, in contrast with previous studies that reported significant associations between diabetes and walkability (9, 55). These variations in findings between studies may be attributed to the use of different measures to assess greenness and street connectivity. However, we observed a significant negative association between adjusted diabetes and neighborhood income in the northern areas and a positive association with the proportion of the foreign population in the southern areas, which highlights the importance of addressing socioeconomic disparities in diabetes (50, 56).

Dyslipidemia showed no significant local associations with characteristics of the social and physical environments. Previous literature on the association between blood lipids and the built environment has often emphasized urban-rural differences, with higher blood lipid levels observed in urban areas (16). Given that our study area was limited to an urban context, it is possible that the associations between dyslipidemia and the environment occur at a broader spatial scale, and thus we may not have sufficient spatial variation within the city to detect them.

Spatial associations between CMRFs and the contextual factors showed heterogeneity across the city. Some associations were consistent in direction but varied in magnitude, while others shifted in sign between areas. This underscores the value of geographically weighted regressions for capturing these intricate, local variations. Interestingly, similar to the findings of Kauhl et al. (56) in northeast Germany, we observed a varying directional association between neighborhood income and diabetes across the city.

We recognized the importance of the multiscale extension of geographically weighted regression (MGWR), particularly for disentangling associations between obesity and the physical and social environments. The GWR model encountered problems with local multicollinearity and inadequately captured the multiple process scales among contextual factors. For diabetes and hypertension, where associations were predominantly global and no multicollinearity problems were identified, the multiscale extension was less critical. Nevertheless, while insights can still be gained from interpreting the GWR results, greater reliance should be placed on the results of the MGWR model due to its improved performance and better handling of multiscale effects (45).

It is noteworthy that although our study revealed substantial differences in contextual factors between high-risk, low-risk, and neutral areas on the log relative risk surfaces for hypertension, diabetes, and obesity, these associations were not fully reflected in the GWR and MGWR models, except for obesity. This divergence could be explained by the fact that the spatial variation in diabetes and hypertension was largely attributable to individual-level characteristics rather than contextual factors.

Policy implications

Several areas identified as high-risk in the log relative risk model align closely with significant local associations determined by the GWR and MGWR models. This congruence enables the formulation of valuable recommendations for targeted preventive public health actions to enhance the living conditions of local populations. Our findings highlight the importance of addressing socioeconomic barriers when designing population-level interventions for hypertension. In particular, we observed a consistent negative association between neighborhood median income and hypertension risk in almost all high-risk areas. For obesity, the large high-risk area in landmark #2 was characterized by a negative association with median income, a positive association with unemployment rate, and a negative association with greenness. Policymakers should consider strategies to improve walkability and increase vegetation in this area while taking into account socioeconomic barriers. In addition, the high-risk area in landmark #1 shows a negative association with neighborhood income and a positive association with the proportion of compulsory education. Although not statistically significant in the MGWR model, the GWR model also indicates a negative association with street connectivity, which should be considered in future policy planning, especially given the proximity to surrounding highways. In essence, a neighborhood with high street connectivity provides multiple route options, reducing travel distances. This promotes an environment for active mobility, which in turn could reduce the risk of obesity (57).

Strengths and limitations

Our study has several strengths. First, we conducted our analysis using individual data from a population-based cohort, which provides a robust basis for assessing spatial variation in CMRFs. The use of health outcomes assessed during medical examinations, rather than relying on self-reported data, helps to mitigate common biases in epidemiological studies (58). Through the analysis of georeferenced home addresses of study participants, we mitigated inherent biases in ecological studies, such as the modifiable unit areal problem (59). Moreover, by adjusting for important individual-level confounders, such as age, sex, socioeconomic status, and country of birth, we reduced the likelihood that observed associations between neighborhood characteristics and health outcomes were solely attributable to unaccounted individual-level factors (20).

Another strength is that we studied four major metabolic risk factors for CVD simultaneously, allowing comparisons of their respective geographic patterns. We also attempted to capture several dimensions of the social and physical environments that may be associated with CMRFs (20, 21), including material deprivation, ethnic composition, environmental exposures such as nighttime noise and air pollution, and walkability.

Our study benefits from the acquisition of environmental characteristics for the year 2015, ensuring temporal alignment with the study period, and we also observed residential stability for a significant proportion of study participants over a 10-year period (from baseline to study period). Despite these considerations, the cross-sectional nature of our study still limits our ability to fully account for participants' cumulative exposures over time.

Although the GWR and MGWR models identified local associations between obesity, hypertension, and diabetes and specific environmental characteristics, their explanatory power was limited. This is partly due to our use of health outcomes previously adjusted for individual confounders (Pearson residuals of logistic regression), which explained 5–10% of the total variance of CMRFs. The contribution of contextual factors, approximately 2.5% for obesity and 1.5% for diabetes and hypertension, was modest compared to individual-level factors, consistent with literature (21, 29). In addition, modeling individual disease risk rather than area-level prevalence introduced noise and overfitting, which contributed to the observed lower R2 values. Despite these limitations, our study may still fail to capture significant individual or contextual predictors of these CMRFs. Examining factors beyond the residential environment and including additional confounding variables may improve the explanatory power of future models and provide more comprehensive insights into the multifactorial determinants influencing CMRFs. From a policy perspective, this approach may also open the way to constructing a 'portrait' of populations susceptible to CMRFs and then using fine-scale area-level data to identify regions within the administrative territory with significant concentrations of such profiles. This proactive strategy could serve as a valuable tool for targeting preventive population health interventions.

Furthermore, it is important to consider the temporal context of our study, which reflects the state of the city in 2017. While the spatial health inequalities observed during the baseline period (2003–2006), the first follow-up (2009–2012), and the second follow-up (2014–2017) remained relatively stable, changes may have occurred since then. A third follow-up (2019–2022) was available, but the examination of participants was significantly affected by the COVID-19 pandemic, which may have introduced bias into the data. In addition, the departure of several participants from the cohort since baseline increases the possibility of deviations from the general population of Lausanne. However, it is noteworthy that we did not detect significant differences in population characteristics between baseline and the second follow-up, except for those related to aging (e.g., occupational activity, physical inactivity, proportion of females, and individuals living alone).

Conclusion

In conclusion, we identified high-risk areas for CMRFs and several associations with specific features of the physical and social environments, independent of individual-level factors. These findings provide an important basis for the design of targeted population-level interventions for cardiovascular disease.

Abbreviations

CVD
Cardiovascular Disease
CMRF
Cardiometabolic Risk Factor
BMI
Body Mass Index
OLS
Ordinary Least Squares
GWR
Geographically Weighted Regression
VIF
Variance Inflation Factor
AIC
Akaike Information Criterion
MGWR
Multiscale Geographically Weighted Regression

Declarations

Ethics approval and consent to participate

The institutional Ethics Committee of the University of Lausanne, which afterwards became the Ethics Commission of Canton Vaud (www.cer-vd.ch) approved the baseline CoLaus study (reference 16/03, decisions of 13th January and 10th February 2003). The approval was renewed for the first (reference 33/09, decision of 23rd February 2009), the second (reference 26/14, decision of 11th March 2014) and the third (reference PB_2018-00040, decision of 20th March 2018) follow-ups. The approval for the entire CoLaus|PsyCoLaus study was confirmed in 2021 (reference PB_2018-00038, 239/09, decision of 21st June 2021). The full decisions of the CER-VD can be obtained from the authors upon request. The study was performed in agreement with the Helsinki declaration and its former amendments, and in accordance with the applicable Swiss legislation (LRH 810.30, approved by the Swiss Federal Parliament on 30th of September 2011). All participants gave their signed informed consent before entering the study.

Consent for publication

Not applicable.

Availability of data and materials

The data of CoLaus|PsyCoLaus study used in this article cannot be fully shared as they contain potentially sensitive personal information on participants. According to the Ethics Committee for Research of the Canton of Vaud, sharing these data would be a violation of the Swiss legislation with respect to privacy protection. However, coded individual-level data that do not allow researchers to identify participants are available upon request to researchers who meet the criteria for data sharing of the CoLaus|PsyCoLaus Datacenter (CHUV, Lausanne, Switzerland). Any researcher affiliated to a public or private research institution who complies with the CoLaus|PsyCoLaus standards can submit a research application to research.colaus@chuv.ch or research.psycolaus@chuv.ch. Proposals requiring baseline data only, will be evaluated by the baseline (local) Scientific Committee (SC) of the CoLaus and PsyCoLaus studies. Proposals requiring follow-up data will be evaluated by the follow-up (multicentric) SC of the CoLaus|PsyCoLaus cohort study. Detailed instructions for gaining access to the CoLaus|PsyCoLaus data used in this study are available at www.colaus-psycolaus.ch/professionals/how-to-collaborate/.

The code used to perform the analyses will be made available on Zenodo with the publication of the paper.

Competing interests

The authors declare that they have no competing interests.

Funding

Anaïs Ladoy is funded by the Direction Générale de la Santé of the state of Vaud (DGSVaud) in the context of the GEOSAN project (Grant Agreement C/20-21/037).

The CoLaus|PsyCoLaus study was supported by unrestricted research grants from GlaxoSmithKline, the Faculty of Biology and Medicine of Lausanne, the Swiss National Science Foundation (grants 3200B0–105993, 3200B0-118308, 33CSCO-122661, 33CS30-139468, 33CS30-148401, 33CS30_177535 and 3247730_204523) and the Swiss Personalized Health Network (grant 2018DRI01).

Authors’ contributions

Conceptualization: AL, PMV, IG, SJ. Methodology: AL, SJ. Data acquisition and curation: PMV, AL. Data Analysis: AL. Writing—original draft preparation: AL. Writing – review & editing: AL, PMV, IG, SG. All authors reviewed and approved the final manuscript.

Acknowledgements

We would like to thank the Direction générale du territoire et du logement (DGTL) of the canton of Vaud for providing us with the cadastral land cover archives. The authors are also grateful to the inhabitants of the city of Lausanne for their voluntary participation in the CoLaus|PsyCoLaus study and to the dedicated staff who contributed to the coordination of the study and the collection of data.

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Figures

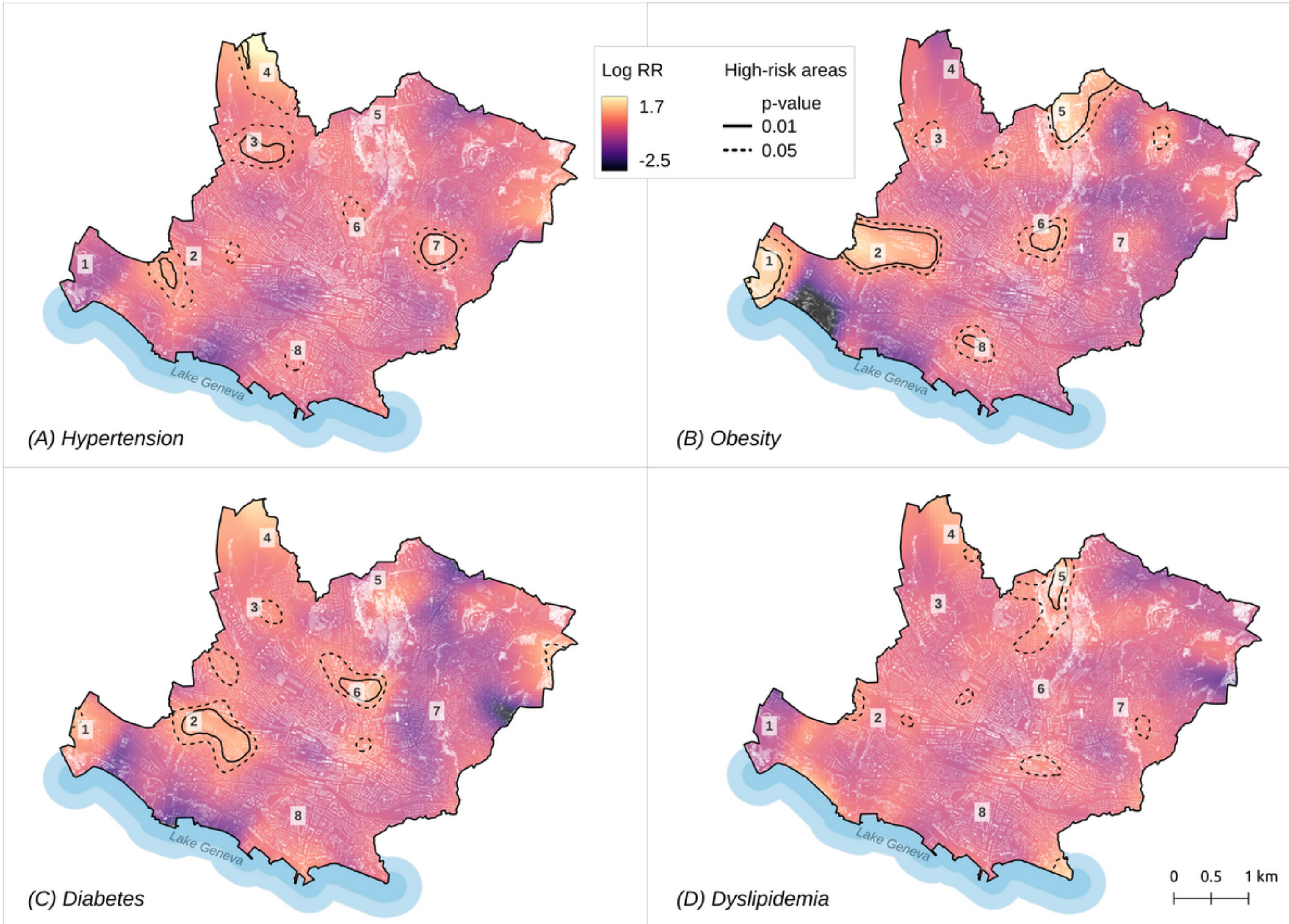

Figure 1

Log relative risk (Log RR) surface of CMRFs: (A) hypertension, (B) obesity, (C) diabetes, and (D) dyslipidemia. Density estimations were performed using Gaussian Kernels with a Bandwidth of 200 meters. High-risk areas were determined by tolerance contours (Tol. Intervals) based on 999 Monte Carlo permutations. Indicative landmarks are shown on the map to help interpret the results (#1-#8). The basemap layer consists of a Digital Heights Model (DHM) from 2012 (Géodonnées Etat de Vaud, 2012), and the maps were generated using QGIS (v. 3.22.16).

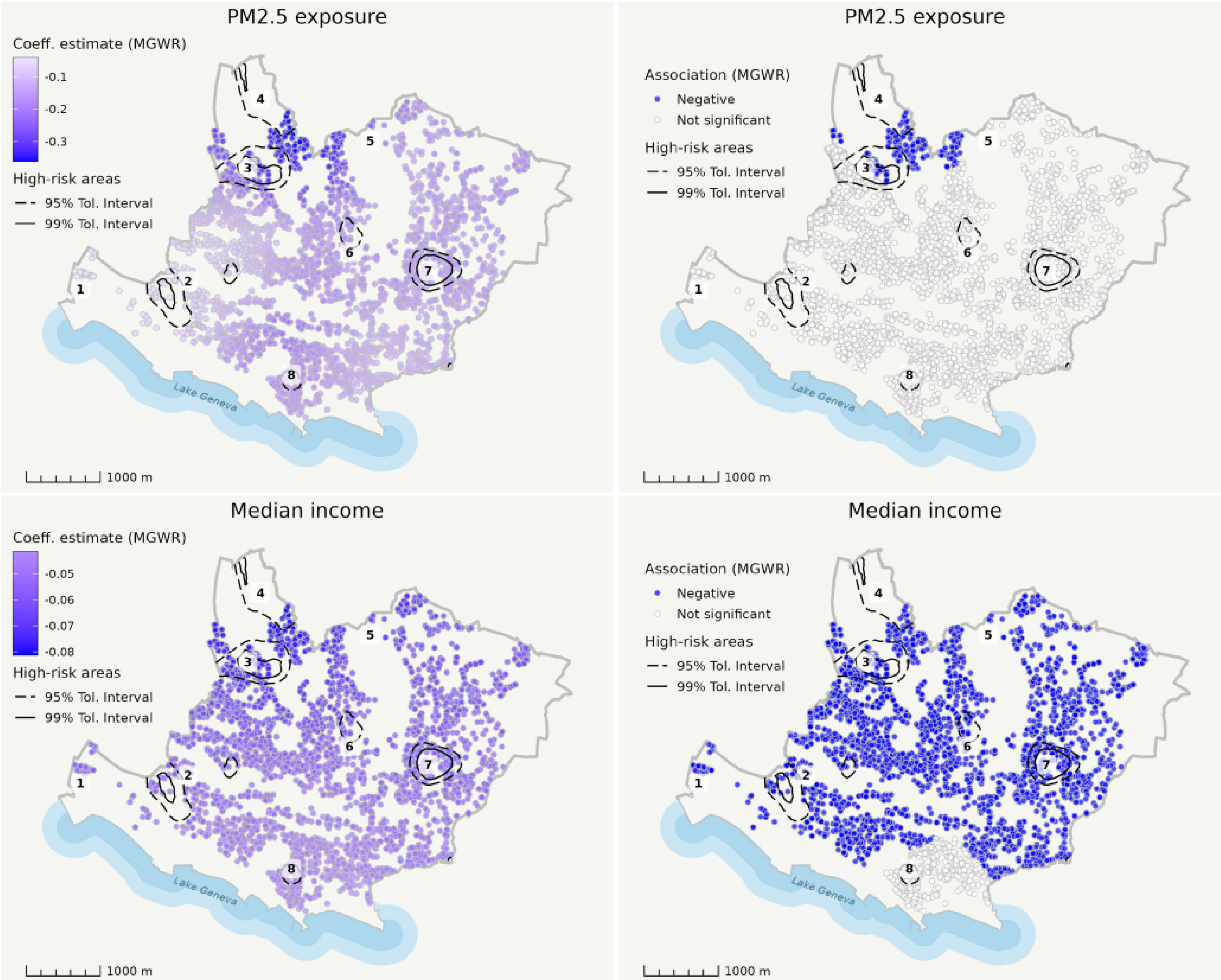

Figure 2

Local contextual determinants of hypertension. The figure shows the results of Multivariate Geographically Weighted Regression (MGWR) highlighting local associations between adjusted hypertension and characteristics of the physical and social environments. Maps in the left column show coefficient estimates reflecting the magnitude of associations with contextual factors, while the right column differentiates these associations by statistical significance: white dots for non-significant, blue for negative, and red for positive associations. Solid and dashed lines delineate areas of high hypertension incidence. Indicative landmarks are shown on the maps to help interpret the results (#1-#8). Only determinants with statistically significant variation based on corrected t-values are shown; others can be found in Supplementary Figure 17, Additional File 1. For privacy reasons, the Digital Heights Model (DHM) base map layer was intentionally excluded.

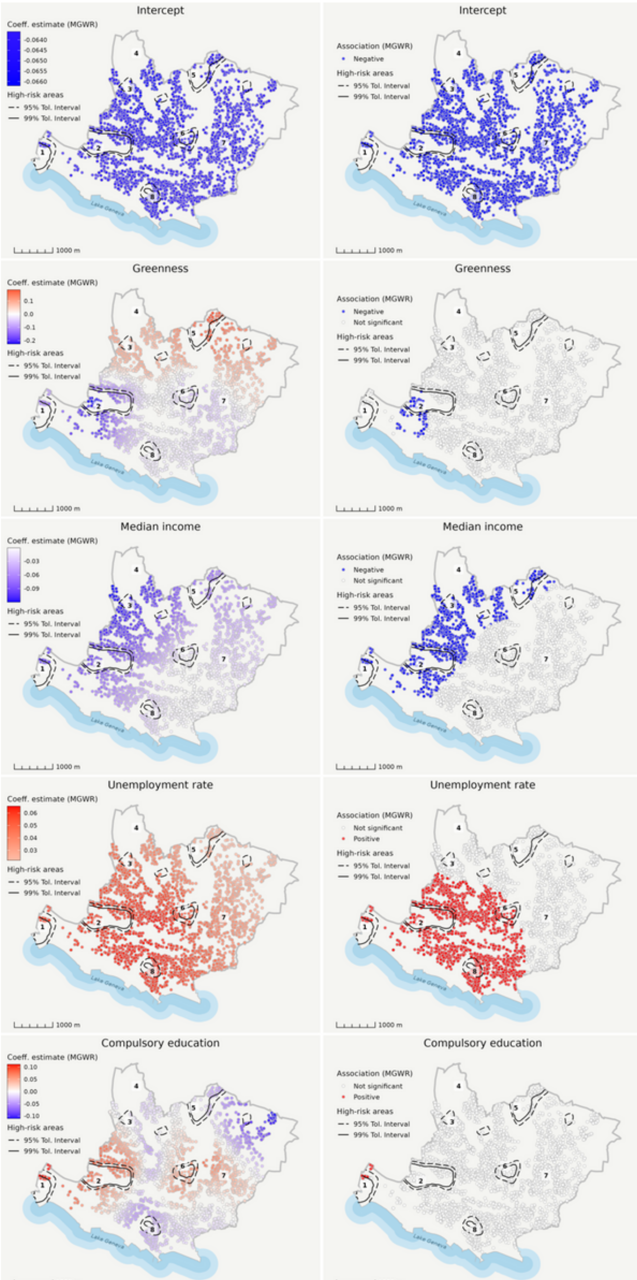

Figure 3

Local contextual determinants of obesity. The figure shows the results of Multivariate Geographically Weighted Regression (MGWR) highlighting local associations between adjusted obesity and characteristics of the physical and social environments. Maps in the left column show coefficient estimates reflecting the magnitude of associations with contextual factors, while the right column differentiates these associations by statistical significance: white dots for non-significant, blue for negative, and red for positive associations. Solid and dashed lines delineate areas of high obesity incidence. Indicative landmarks are shown on the maps to help interpret the results (#1-#8). Only determinants with statistically significant variation based on corrected t-values are shown; others can be found in Supplementary Figure 18, Additional File 1. For privacy reasons, the Digital Heights Model (DHM) base map layer was intentionally excluded.

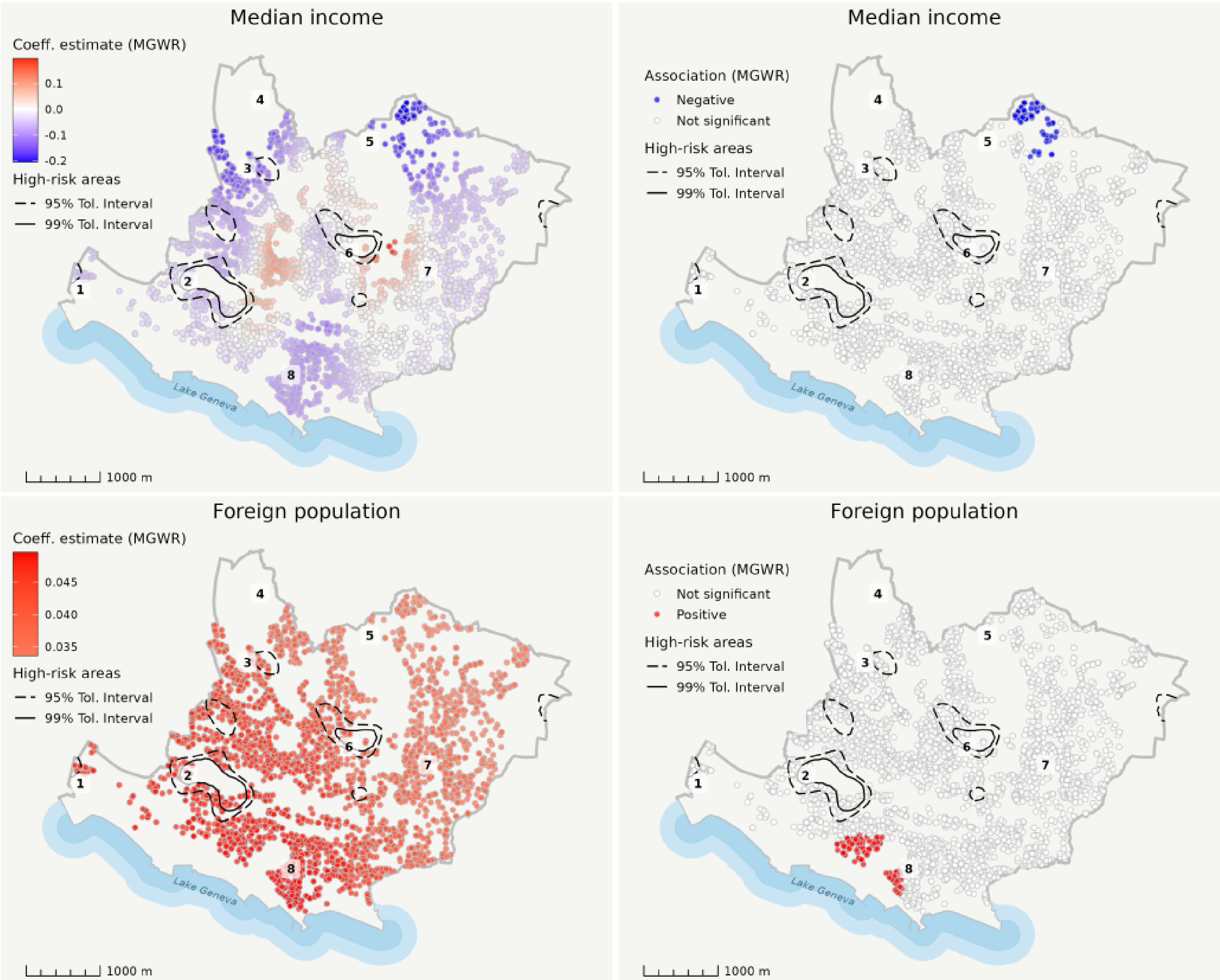

Figure 4

Local contextual determinants of diabetes. The figure shows the results of Multivariate Geographically Weighted Regression (MGWR) highlighting local associations between adjusted diabetes and characteristics of the physical and social environments. Maps in the left column show coefficient estimates reflecting the magnitude of associations with contextual factors, while the right column differentiates these associations by statistical significance: white dots for non-significant, blue for negative, and red for positive associations. Solid and dashed lines delineate areas of high diabetes incidence. Indicative landmarks are shown on the maps to help interpret the results (#1-#8). Only determinants with statistically significant variation based on corrected t-values are shown; others can be found in Supplementary Figure 19, Additional File 1. For privacy reasons, the Digital Heights Model (DHM) base map layer was intentionally excluded.

Supplementary Files

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