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Green and Grey: The Association Between the Built Environment and Diabetes Prevalence in Israel

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Taub Center Research and Policy Initiative for Environment and Health

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Background

Diabetes mellitus is a chronic disease comprising a heterogeneous group of disorders characterized by persistent hyperglycemia (high blood sugar). The disease has several forms, the most common of which (about 90% of patients) is type 2 diabetes mellitus. Because this form of diabetes is influenced by physical activity and dietary habits, it is not surprising that it displays both socioeconomic and spatial variation: the likelihood that an individual will develop diabetes varies across countries, cities, and localities,[1] and even across areas within them (Baker et al., 2015; Cuadros et al., 2021). In Israel as well, differences in diabetes prevalence can be observed between and within localities (Map 1). The map of the southern Sharon region in Israel shows, for example, that in the city of Netanya the prevalence of diabetes varies from one area to another, and that prevalence rates are particularly high in Arab localities.

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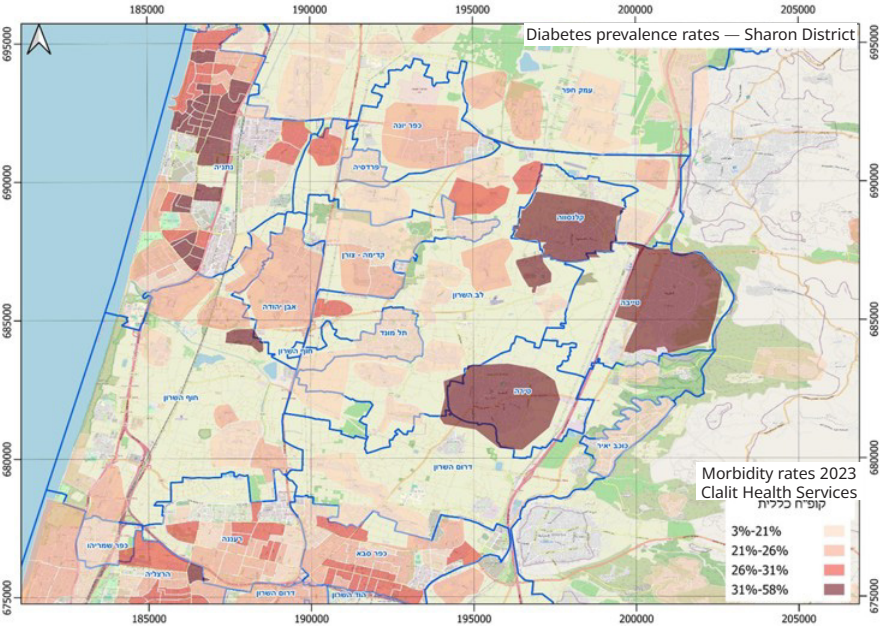
1 "Locality" is the standard translation of the Hebrew term ***yishuv***, which refers to a residential area of any size: from a hamlet of 50 people to a city of a million. There is no direct equivalent in English. Here, locality covers both towns and cities.

Map 1. The share of diabetes partially adjusted for age in the statistical geographic areas — The Southern Sharon area, 2023



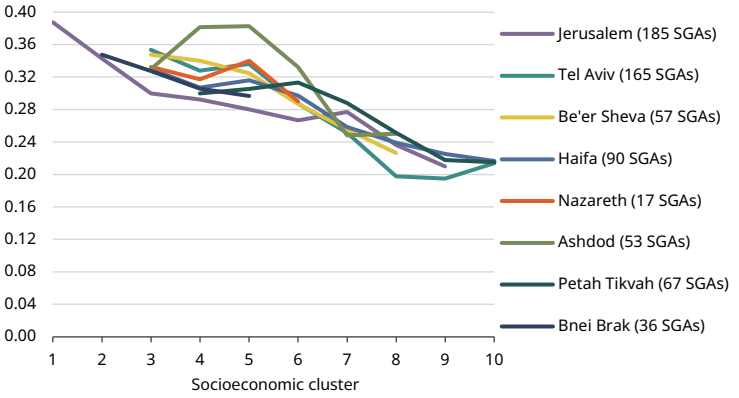
Note: The number of individuals with diabetes in each statistical area is divided by the number of insured individuals aged 45 and over in that statistical area.

Source: Clalit Health Services

A substantial body of scientific research has sought to understand the factors underlying these spatial differences in diabetes prevalence. In the Israeli context, the first explanation attributes them to differences in socioeconomic status, poverty rates, income, and education. At the individual level, low socioeconomic status is associated with suboptimal health behaviors (poor diet and a sedentary lifestyle) and inappropriate use of health services. At the environmental level, there may be differences in access to healthy food, in factors that facilitate regular physical activity, and in conditions that help reduce psychological stress.

Figure 1 shows that diabetes prevalence is higher in areas with lower scores on the socioeconomic index.[2] For example, in Ashdod, diabetes prevalence is particularly high in clusters 4 and 5 and declines sharply in clusters 6 and 7. A similar, though less pronounced, decline in diabetes prevalence from the middle to the higher clusters can be observed in Nazareth, Tel Aviv, Haifa, and Petah Tikva.

Figure 1. Average diabetes prevalence among Clalit Health Service members, by socioeconomic cluster of the statistical area, 2023



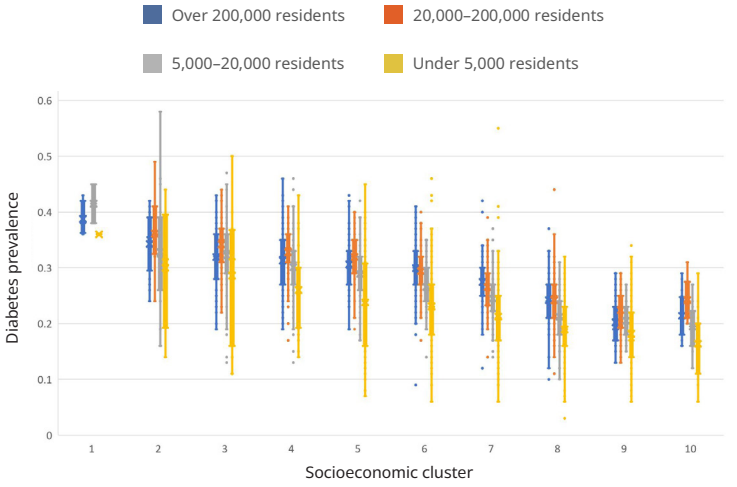
Source: Clalit Health Services

Locality population size is also associated with spatial variation in diabetes prevalence. Figure 2 shows that the highest prevalence rates are observed in localities with populations of 20,000–200,000, and that, in general, prevalence declines as locality population size decreases. Rates are also lower in the largest localities. Several factors may explain these patterns. There may be overlap with socioeconomic status, discussed above, or with access to health services. Environmental factors, such as lower levels of air pollution and greener surroundings, may also help explain the spatial differences in diabetes prevalence.

2 The socioeconomic index used in this study was obtained from Points Location Intelligence, a company that also provides geographic data to the Ministry of Health and the health funds. It provides a more accurate assessment of the socioeconomic status of the Haredi and Arab populations than the index developed by Israel's Central Bureau of Statistics (CBS). We thank Points for making its index available for this study.

This last possibility forms the basis of the present study: our goal is to examine the association between the built environment and diabetes prevalence in Israel.

Figure 2. Diabetes prevalence by socioeconomic cluster and locality population size



Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Clalit Health Services

The association between the built environment and diabetes prevalence rates

Scientific research indicates that environmental exposures in the built environment, such as exposure to nature and green space, transportation, air pollution, and noise, can explain some of the spatial differences in diabetes prevalence in urban and semi-urban areas (Ccami-Bernal et al., 2023). A recent systematic review examining the strength of the scientific evidence linking green space with various health conditions classified the causal association between exposure to green space and diabetes prevalence as highly suggestive and found a 12% reduction in diabetes prevalence (confidence interval [hereafter CI] 11%–14%) for each one-interquartile-range increase in green space (Xie et

al., 2024).[3] A study that followed approximately 212,000 women for about 25 years found that exposure to green space in the residential environment was associated with a 4% reduction in diabetes incidence (Fiffer et al., 2025). An 18-year prospective cohort study found that the likelihood of developing diabetes among people living in greener environments was 21% lower than among those living in less green environments (a one-interquartile-range difference in green space) (Doubleday et al., 2022). These analyses controlled for other variables that could explain the observed association, such as population sector,[4] socioeconomic status, smoking, diet, air pollution, and others.

Several biological mechanisms link environmental exposures in the built environment with diabetes. Among the physical mechanisms associated with green environments are direct effects through reductions in air pollution and noise, and indirect effects insofar as green environments are often shaded and aesthetically pleasing and encourage walking and physical activity in the residential area, thereby reducing obesity and diabetes rates (Feyissa et al., 2024; Xie et al., 2024b; Yang & Zhou, 2020). Exposure to green space is also associated with reduced psychological stress, which is itself a risk factor for the development of diabetes, and enables the formation of broader social ties within the urban residential environment (Hackett & Steptoe, 2017; Feyissa et al., 2024).

Another dimension of the built environment is the share of built-up area relative to other types of land cover. This dimension, measured by the proportion of impervious surfaces[5] in a given area, captures another aspect of urban quality of life—higher air temperatures resulting from the formation of urban heat islands, traffic congestion accompanied by air pollution and noise, and deterioration of urban aesthetics. All of these have been linked in the literature to higher rates of cardiovascular disease and diabetes, as well as to mental health conditions such as intrusive thoughts and psychological stress (Bratman et al., 2021; Lane et al., 2015).

3 Green space is measured using the NDVI (Normalized Difference Vegetation Index). See further details in the Data section below.

4 We use the word "population sector" since it is the standard translation of the Hebrew term ***migzar***. When used to describe population groups in the Israeli context, "sector" refers to identity that combines both ethnic and religious markers (for example, Jews, Arabs, Druze, Other).

5 Built surfaces through which rainwater and surface runoff cannot infiltrate, such as roads, roofs, and parking lots.

Urban quality of life in Israeli planning policy

In recent decades, the State of Israel has adopted an approach to urban planning that seeks to curb suburbanization, strengthen urban continuity, and preserve open spaces, while anchoring these principles in national outline plans and official policy documents (Planning Administration, 2016). Within this framework, the urban environment is viewed not only as a space of buildings and infrastructure, but as a social-environmental system that shapes residents' everyday living conditions and health. Planning principles emphasize compact urban development, mixed land use, access to public open spaces and recreational areas, and the preservation of continuous green vegetation and shade in urban and interurban spaces, based on recognition of their potential contribution to reducing heat exposure, encouraging physical activity, and strengthening health and mental and social well-being. In this sense, national planning principles address not only the spatial distribution of development, but also the quality of the everyday living environment in which environmental exposures occur and health behaviors are shaped.

The urbanism chapter of Israel's Spatial Strategic Plan expands on this approach and emphasizes that, because more than 90% of Israel's population lives in urban localities, the quality of the urban environment is a fundamental factor shaping the overall populations' living conditions, access to opportunities, and residents' environmental exposures (Bar et al., 2023). The document defines "good urbanism" through principles of connectivity and continuity in the street network, mixed uses, compact planning, access to public transportation, and the integration of green and blue infrastructure, while emphasizing the importance of shaded, continuous, and accessible streets and public spaces that support walking, reduce dependence on private vehicles, and help address heat loads and climate risks. From a health perspective, this framework illustrates that the potential health effects of open spaces and the public realm do not derive solely from the allocation of land for public open spaces, but also from how such spaces are designed, integrated into the urban fabric, shaded, maintained, and made accessible for everyday use. A nationwide study at the statistical-area level provides an opportunity to describe the spatial structure of environmental exposures in Israel and to identify planning and implementation mechanisms that may contribute to the narrowing—or widening—of social disparities in health, including in diabetes prevalence.

Study aims

In this study, we examine whether environmental exposures in the built environment—green space and impervious surfaces—are associated with diabetes prevalence beyond differences in age, population sector, and socioeconomic status across areas in Israel.

Data

The study population comprises 2,835 inhabited statistical geographic areas (SGAs) in Israel.[6] As of 2022, the total number of SGAs in Israel was 3,496. Data from Clalit Health Services were available for 3,033 SGAs; of these, SGAs with fewer than 100 residents and SGAs for which the health fund data or environmental data were missing or erroneous were excluded.

Outcome variables

The analysis focuses on the prevalence of diabetes among Clalit Health Services members in each SGA in 2022–2023 (calculated as the number of diabetes cases relative to the number of Clalit members in each SGA).[7] These data do not distinguish among types of diabetes—type 2 diabetes, type 1 diabetes, and gestational diabetes—but, as noted in the introduction, about 90% of diabetes cases are type 2 diabetes.

Exposure variables

- ***Green space*** in each SGA is measured using the Normalized Difference Vegetation Index (hereafter NDVI), calculated from Sentinel-2 satellite images at a resolution of 10 m. This index has been found to correlate with subjective assessments of how green the environment is overall (Markevych et al., 2017; Rhew et al., 2011). The index ranges from -1 to 1. Negative

6 SGA boundaries were obtained from Points Location Intelligence.

7 The data were obtained through Freedom of Information requests submitted to Clalit and Maccabi health funds. We chose to use Clalit Health Services data which provides health coverage to more than 50% of Israelis and represents all socioeconomic levels of the population relatively equally..

values represent water or snow, while the range relevant to the built environment is 0 to 1. The higher the value, the greener the area, with the increase being linear up to approximately NDVI = 0.4 (the range relevant to the vast majority of built-up areas in Israel) (Markevych et al., 2017; Small, 2001). Green space in a statistical area is measured as the average of all 10 × 10 m pixels within the SGA.

- ***Variation in green space*** within an SGA is the standard deviation of the NDVI values across all pixels in the SGA.
- ***The percentage of built-up land cover*** in each SGA was quantified using a model developed by the European Space Agency (ESA), which provides global high-resolution land-cover mapping at a resolution of 10 m. The tool maps built-up land cover on the basis of Sentinel-2 satellite data from the European Union and other sources. The model classifies the land surface into different land-cover types—impervious surfaces,[8] various types of green cover (trees, agriculture, fields, etc.), barren land, water bodies, and ice. The map covering the territory of Israel was examined according to the division into SGAs, and the proportion of built-up area in each was calculated. In regions with high rainfall and abundant vegetation, the NDVI and the impervious surface index (ESA) tend to be strongly negatively correlated (Martins et al., 2018). In arid regions, by contrast, the relationship between them is considerably weaker. In the present study, in which both indices were measured using satellite imagery at a spatial resolution of 10 meters, a moderate negative correlation was found between them (ρ = -0.5). In desert regions or areas with less vegetation, the impervious surface index is also important for distinguishing between green natural areas and natural or undeveloped areas that lack vegetation. It is important to note that, in terms of measurement accuracy using satellite imagery, green space can be measured more accurately than impervious surfaces, for technical reasons related to the characteristics of the reflected radiation signal.
- ***The share of Clalit Health Services members aged 45 and over out of all Clalit members in each statistical area*** (2023). This variable was included in the models to account for differences in age structure across statistical areas, since diabetes cases were counted across all age groups.

8 Impervious surfaces include buildings, roads, railways, industrial structures.

Covariates

These variables may be associated with the diabetes outcome or with age at diabetes onset, as well as with the environmental exposures.

- ***Socioeconomic status data*** for each SGA for 2013 were obtained from a company called "Points." The data are based on the CBS socioeconomic index, which includes demographic composition, education, standard of living, employment, and benefits, supplemented by data on private consumption, health and morbidity, financial indicators, and real estate. The index is updated on an ongoing basis and is also calculated for newly built areas for which the CBS index has not yet been calculated. The index is used by the Ministry of Health and the health funds. An additional control variable is mean age at diabetes diagnosis (the average age at diagnosis among all individuals diagnosed in the SGA). Age at diagnosis is expected to be relatively young both in more polluted areas and in more highly educated areas (because of greater access to health services). Accordingly, age at diagnosis may capture an additional dimension of socioeconomic status that is not fully represented in the socioeconomic index.

- ***Raw spatial variables*** include dummy variables for locality population size (as of 2022), divided into those with up to 10,000 residents, 10,000–100,000 residents, and more than 100,000 residents.

- ***Road-network connectivity*** is an essential component in measuring walkability (as a proxy for physical activity). High connectivity, characterized by a large number of street segments between intersections, increases accessibility to a variety of destinations. The higher the connectivity, the greater the number of street segments between intersections and the higher the level of accessibility. Connectivity was calculated as the number of street segments between intersections divided by the number of intersections, based on Central Bureau of Statistics data for 2017.[9]

- ***Land-use mix*** (for example, residential, commercial, park, and educational and cultural institutions) in the built environment increases people's tendency to walk more and use private vehicles less. Land-use mix was calculated by

9 Connectivity data for 2017 and land-use data for 2021 were obtained from the CBS and processed by Dr. Rakefet Shafran-Nathan.

dividing the percentage of each land use by the number of discrete land uses present in the SGA, based on the CBS 2021 land-use layer.

- ***Nitrogen dioxide (NO_2) concentration and particulate air pollution ($PM_{2.5}$)*** were calculated using a model developed by the Ministry of Environmental Protection that takes into account emission sources, measurements from monitoring stations, and land use. These variables were obtained as continuous measures and averaged for each SGA. Nitrogen dioxide is an air pollutant used as a marker of traffic-related air pollution. Particulate air pollution has been found to be associated with higher diabetes prevalence.

- ***Bird species richness*** is a measure of the number of bird species recorded in a statistical area. In health research, this measure serves as a proxy for exposure to and experience of nature, rather than as a direct measure of the ecological quality of a habitat. The measure captures several components that cannot be disentangled: sensory exposure to birds (their songs and visibility); habitats that support bird populations, such as diverse vegetation, mature trees, and water sources; and relatively low levels of traffic noise and air pollution, which birds also tend to avoid (Buxton et al., 2024; Methorst, 2024; Methorst et al., 2021).[10]

Statistical methods

In the descriptive stage of the study, univariate associations between diabetes prevalence and the explanatory variables were examined. In the second stage, generalized linear models (GLMs) were used. These models extend linear models by allowing the outcome variable to follow a wide range of distributions. We used models assuming a negative binomial distribution. We chose this distribution, an extension of the Poisson distribution, because the Poisson model exhibited substantial overdispersion, resulting in confidence intervals that were too narrow.

10 These data were obtained from Dr. Enav Vidan of Prof. Uri Roll's laboratory at Ben-Gurion University of the Negev.

The models examining the associations between measures of built-environment and diabetes prevalence were adjusted for several control or confounders: mean age at diabetes diagnosis among individuals with diabetes in the SGA, population sector, ethnic origin, socioeconomic status, locality population size, street-network connectivity, land-use mix, and an interaction between socioeconomic status and the level of greenness. The confounders included in the study were those correlated with the exposure variables (green space and impervious surfaces), as well as variables found to be associated with diabetes rates in the univariate analysis and to affect the model coefficients.[11] Each of these is associated with diabetes prevalence in bivariate analysis.

Each SGA was analyzed using generalized additive models (GAMs), whose flexible functional form captures nonlinear relationships and allows for non-monotonic dynamics, crucial in this case, as in epidemiological and demographic research in general. Population sector, locality population size, and socioeconomic status at the SGA level (in quintiles) were included as categorical variables. Street-network connectivity, land-use mix, greenness (satellite-based NDVI), variation in NDVI within the statistical area, the share of impervious surfaces, and fine particulate matter (PM2.5) concentration and mean annual NO_2 concentration were fitted using splines ($k = 4$) to characterize and quantify nonlinear associations. Because the Haredi population tends to live in areas with less green space and consumes more sugar-sweetened beverages, which contribute to the development of diabetes, the model also examined the degree of Haredi population concentration in each statistical area, divided into three categories: no Haredi population, low to moderate Haredi concentration, and Haredi majority. Compared with areas with no Haredi population, diabetes prevalence was 13.7% higher in statistical areas with a low to moderate Haredi concentration ($p < 0.001$) and 4.3% lower in Haredi-majority statistical areas ($p < 0.001$). Since including the degree of Haredi population concentration in the model did not alter the associations with the built environment variables, this variable was excluded from the final model.

11 This is an important variable because it ensures that the number of cases (dependent variable) will be proportional to the population of the SGA.

It is important to note that, because several years may pass between the development of diabetes in the body and the appearance of clinical signs of the disease, an effort was made in this study to model the exposure data before development of the outcome, thereby establishing a temporal sequence consistent with a cohort study. The diabetes outcome was measured in 2022–2023, socioeconomic status by SGA was measured in 2013, and green space was measured in 2018. Air pollution was measured in 2022, but changes over time in the spatial variation in air pollution are known to be negligible (Sadeh et al., 2024).

Collinearity among the model variables was assessed using the "mgcv" and "performance" packages in R.

Results

The descriptive stage

To identify and describe the association between diabetes and the proposed variables, Table 1 divides all SGAs in the sample into quartiles according to diabetes prevalence—in the first quartile, prevalence does not exceed 20%, while in the fourth quartile it is above 31%. The findings show, first and foremost, that diabetes prevalence is closely and linearly associated with the socioeconomic status of the SGA and with population group, consistent with the findings presented in Figure 1 and Map 1: in 68.6% of SGAs with an Arab majority, diabetes prevalence falls in the highest quartile, compared with 20% of SGAs with a Jewish majority.

Other notable findings show a positive association between diabetes prevalence and the proportion of built-up area (impervious surfaces), traffic-related air pollution (NO_2), and the degree of street-network connectivity. However, the association is not linear for any of these three variables: it is stronger across the lower quartiles than across the upper quartiles. The findings also show that the greener the environment and the greater the bird species richness in the SGA, the lower the diabetes prevalence—and this association does appear to be linear.

Table 1. Characteristics of the residential environment, by quartile of diabetes prevalence, 2023

T2D rate, Clalit	3%–21%	21.1%–26%	26.1%–31%	31.1%–65%	p
Number of geographic areas (SGAs)	709	709	709	708	
SES cluster (1-10), 2013 average (SD)	6.9 (1.8)	6.5 (1.8)	5.6 (1.6)	4.3 (1.6)	<0.01
Average age at onset, average for 2023 (SD)	53.6 (6.3)	55.2 (4.6)	55.8 (3.3)	54.4 (5.2)	<0.01
Population sector (SGAs)					<0.01
Jews	701 (98.9)	679 (95.8)	655 (92.4)	507 (71.6)	
Non-Jews	8 (1.1)	30 (4.2)	54 (7.6)	201 (28.4)	
Fine particulate matter, $PM_{2.5}$ micrograms/m^3, average (SD)	16.9 (1.5)	17.1 (1.7)	17.00 (1.7)	17.2 (1.6)	0.18
Nitrogen dioxide NO_2 micrograms/m^3, average (SD)	7.46 (6.13)	10.96 (6.95)	12.07 (6.63)	12.09 (6.25)	<0.01
Nitrogen dioxide (SGAs [%]), $No_2 \geq 10$	224 (31.6)	386 (54.4)	459 (64.7)	450 (63.6)	<0.01
NDVI, average (SD)	0.247 (0.085)	0.226 (0.078)	0.212 (0.062)	0.183 (0.062)	<0.01
NDVI SD, average (SD)	0.131 (0.036)	0.132 (0.034)	0.129 (0.031)	0.121 (0.034)	<0.01
Bird species richness (median [25 percentile, 75 percentile])	15.0 [6.8, 28.9]	13.3 [6.0, 27.0]	9.0 [3.9, 19.8]	6.5 [3.0, 15.3]	<0.01
Connectivity, average (SD)	1.13 (0.66)	1.38 (0.73)	1.71 (0.75)	1.74 (0.76)	<0.01
Impervious surfaces (% of area SGAs) (median [25 percentile, 75 percentile])	35.1 [24.0, 52.8]	53.2 [35.3, 79.0]	75.8 [48.7, 89.5]	83.0 [54.3, 93.3]	<0.01
Mixed land use, average (SD)	0.29 (0.14)	0.31 (0.14)	0.32 (0.15)	0.35 (0.16)	
Locality population size (%)					<0.01
Up to 10,000	510 (71.9)	279 (39.4)	150 (21.2)	128 (18.1)	
10,000–100,000	105 (14.8)	201 (28.3)	233 (32.9)	229 (32.3)	
Over 100,000	94 (13.3)	229 (32.3)	326 (46.0)	351 (49.6)	

Notes: n = 2,835. P-value indicates the statistical significance of the differences between the values of each variable across SGA diabetes-prevalence levels.

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points

Multivariable models

The association between living in a greener environment and diabetes prevalence

The results of the regression model examining the association between green space and diabetes prevalence are presented in Appendix Table A1. Here we present the predicted risk ratio (RR) values derived from the model coefficients.

An association was found between green space in statistical areas and diabetes prevalence. In greener areas—those with NDVI values at or above the median—the greener the residential environment, and thus the greater the exposure to green space, the lower the likelihood of having diabetes relative to areas at the 10th percentile of green space exposure.

Model 1, adjusted for population sector, age, the share above age 45, and socioeconomic status, serves as the baseline estimate. The model findings indicate a clear decline in risk: moving from the 10th percentile, the median, the 75th percentile, and the 90th percentile of green space (NDVI), the RR declines to 0.96, 0.90, and 0.84, respectively.

Additional explanatory variables were added in each model. Model 2 adds locality population size. Model 3 adds street-network connectivity and land-use mix. Model 4 adds air pollution. After the addition of the variables in Model 2, the downward trend becomes weaker (less steep) but remains stable in Models 3 and 4. In other words, after adjustment for other variables, the association between NDVI and diabetes includes a spatial component related to land use, roads, and pollution. Adjusting for these variables explains approximately 60% of the association at the 90th percentile (the risk ratio moves from 0.84 to 0.93), with most of the attenuation occurring when locality population size is added in Model 2. However, the association remains statistically significant even in Model 4. This finding reinforces the impression that exposure to green space is independently associated with a lower risk of diabetes, regardless of the variables for which the model was adjusted.[12]

12 It is important to note that in a model without street-network connectivity and land-use mix but with air-pollution variables, the results are similar to those in Models 3 and 4. This means that, in this model, it is not possible to disentangle the explained variation attributable to the built-environment variables (land-use mix, street-network connectivity, and air pollution), and that all of these play a role in the association with diabetes. Nevertheless, the association with green space remains protective even after their inclusion in the model.

Table 2. Predicted Risk Ratio (RR) for the association between green space and diabetes at different NDVI percentiles, relative to statistical areas at the 10th percentile (NDVI = 0.13) (n = 2,673)

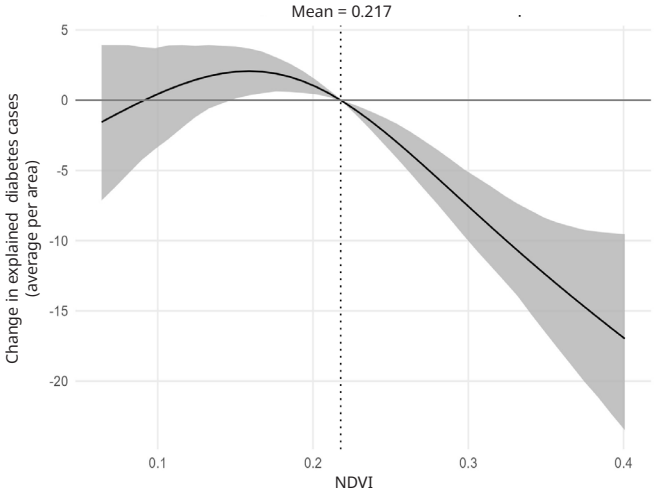
	25th percentile (NDVI = 0.17)	Median (NDVI = 0.22)	75th percentile (NDVI = 0.28)	90th percentile (NDVI = 0.33)
Model 1: Adjusted for age, population sector, SES	1.00 (0.99, 1.01)	0.96 (0.95, 0.98)	0.90 (0.88, 0.91)	0.84 (0.81, 0.86)
Model 2: Additional adjustment for locality population size	1.01 (1.00, 1.02)	0.99 (0.98, 1.01)	0.96 (0.94, 0.98)	0.91 (0.89, 0.94)
Model 3: Additional adjustment for connectivity and land use mix	1.01 (1.00, 1.02)	1.00 (0.98, 1.02)	0.97 (0.95, 0.99)	0.93 (0.90, 0.95)
Model 4: Additional adjustment for air pollution	1.00 (0.99, 1.01)	0.99 (0.98, 1.01)	0.97 (0.94, 0.99)	0.93 (0.91, 0.96)

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points

Figure 3 presents the predicted difference in diabetes prevalence (number of cases) in each SGA as a function of NDVI, relative to a statistical area with an average NDVI value. In statistical areas with below-average NDVI values, no reduction in diabetes prevalence was observed. Above the average, the predicted number of cases declines gradually.

In the fully adjusted model (Table 2, Model 4), the estimated risk ratio for diabetes in statistical areas at the 75th percentile of NDVI (0.28), compared with those at the 10th percentile (0.13), is approximately 0.97 (95% CI: 0.94–0.99). For statistical areas at the 90th percentile (0.33), the risk ratio is approximately 0.93 (95% CI: 0.91–0.96). These findings indicate a reduction of approximately 3%–7% in diabetes rates in greener areas compared with less green areas. In any case, about 97% of the Israeli population lives in SGAs with an NDVI value below 0.4 (and nearly 80% live in SGAs with a value below 0.3). Accordingly, the association between green space and diabetes remains predominantly protective in the general population.

Figure 3. Predicted difference in the number of diabetes cases associated with changes in the NDVI



Note: The graph shows results for Model 4 with 95% confidence intervals.

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points

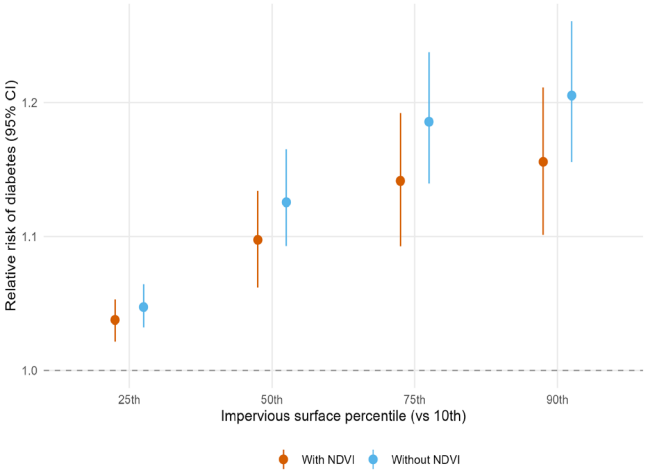
The association between living in areas with more impervious surfaces and diabetes prevalence

It is also important to examine the association between diabetes and environments with a higher proportion of impervious surfaces (such as roads and buildings). These areas are correlated with higher levels of air pollution, noise, and ambient temperature, the latter caused in part by the formation of urban heat islands.

The results of the regression model examining the association between living in an environment with a high proportion of impervious surfaces and diabetes prevalence are presented in Appendix Table A2. Here we focus on the predicted estimates derived from the model coefficients.

The study findings show that as the proportion of impervious surfaces increases, the risk of diabetes also increases (Figure 4). At the 75th percentile of the built environment measure (87% built-up land), diabetes prevalence is 19% higher (95% CI: 14%–24%) than at the 10th percentile (25% built-up land). When green space is added to the model, the association weakens slightly, with a 14% higher risk of having diabetes (95% CI: 9%–19%) at the 75th percentile of the built environment measure compared with the 10th percentile. These findings suggest that only a small part of the association between densely built-up environments and diabetes can be explained by a lack of green space, while most of the association remains even after adjusting for NDVI.

Figure 4. Risk of diabetes at different percentiles of the built environment, relative to the 10th percentile of the built-environment index

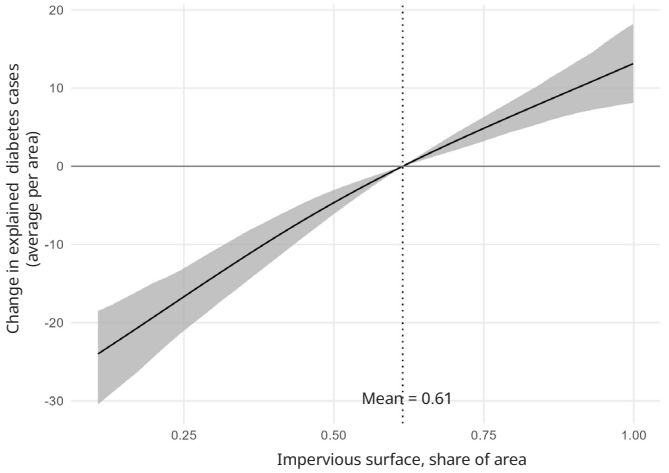


Notes: The graph shows results for Model 4 with NDVI adjusted for population sector, age at diabetes onset, socioeconomic status, locality size, district, street-network connectivity, land use, and air pollution.

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points

Figure 5 presents the predicted change in the number of diabetes cases associated with changes in the proportion of each SGA covered by impervious surfaces. In general, a higher share of built-up areas is associated with higher diabetes prevalence across the entire range of values, and the association is nearly linear: the increase in the predicted number of cases levels off slightly only in the most densely built-up areas. The full statistical model is presented in Appendix Table 2.

Figure 5. Predicted change in the number of diabetes cases for each 10% change in the built environment



Note: The figure presents the results of the model without adjustment for green space.

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points

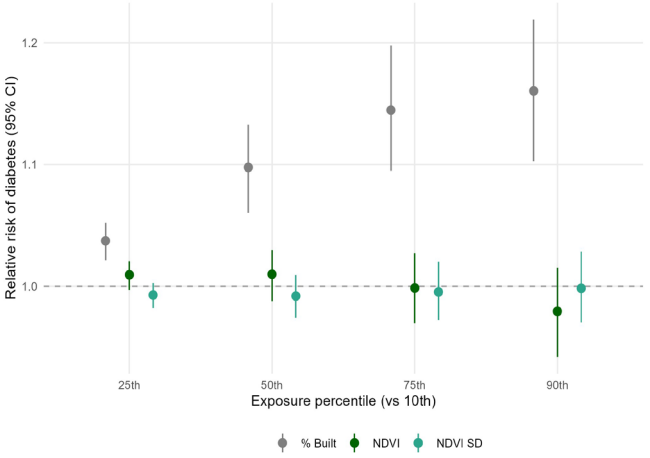
The association between variation in green space by SGA and diabetes prevalence in the SGA

The standard deviation of NDVI across pixels within a statistical area reflects the degree of variation in the green environment of that area. A low standard deviation indicates uniformity in the level of vegetation within the statistical area, which may reflect either uniformly green areas or areas with little vegetation. A high standard deviation indicates that the statistical area contains green spaces, such as parks or gardens, alongside built-up areas with little or no vegetation. In ecological studies such as this one, where diabetes rates and environmental exposures are measured at the statistical area level rather than the individual level, the proportion of green space and the degree of its heterogeneity within the statistical area capture different aspects of the local green environment. Because these two measures are interrelated, we examined their association with diabetes jointly.

The results of the full regression model examining the association between the proportion of green space, variation in green space, the proportion of built-up area, and diabetes prevalence are presented in Appendix Table A3. Figure 6 presents the predicted estimates derived from the model coefficients. The analysis shows that when all three measures are included in the same model, only the share of impervious surfaces is consistently associated with diabetes prevalence: the RR at the 90th percentile relative to the 10th percentile is 1.16 (95% CI: 1.10–1.22). No association was found between variation in green space and diabetes (RR at the 90th percentile: 1.00; 95% CI: 0.97–1.03), and the association between NDVI itself and diabetes prevalence is also not statistically significant in this model (RR: 0.98; 95% CI: 0.94–1.02). However, these findings do not establish that green space is unrelated to diabetes, since NDVI and impervious surfaces are correlated (Spearman's rho = 0.53, $p < 0.001$), making it difficult to disentangle their respective contributions to diabetes prevalence.[13]

13 Concurvity among the model variables was examined. It was moderate for NDVI and high for impervious surfaces (r = 0.85), primarily due to the association with street network connectivity. The correlation between NDVI and impervious surfaces was moderate (r = -0.53). Consequently, it is not possible to fully disentangle the independent contributions of each exposure.

Figure 6. The association between the percentage of green space, variation in green space, and the percentage of built-up area and the risk of diabetes



Notes: The model included mean green-space coverage, the standard deviation of green-space coverage, and the percentage of built-up area in each statistical area, and was adjusted for ethnicity, age at diabetes onset, socioeconomic status, locality size, district, street connectivity, land use, and air pollution.

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points

Discussion

In this study, we show that spatial variation in diabetes prevalence in Israel may also be associated with characteristics of the built environment and the environmental exposures arising from them. We found that characteristics of the physical environment surrounding residential areas in Israel are significantly associated with diabetes prevalence, a disease affecting approximately 700,000 people in Israel. This association remains after adjustment for differences in age, population sector, and socioeconomic status.

Two main findings emerge from the study. ***First***, Greater exposure to green space within a statistical area is associated with lower diabetes prevalence in greener areas. Compared with the 10th percentile, diabetes prevalence is approximately 3% lower at the 75th percentile and 7% lower at the 90th percentile, respectively, even after adjustment for connectivity, land-use mix, and air pollution.

Second, An approximately 19% increase in diabetes risk was observed among residents of areas at the 75th percentile of the built environment measure compared with those at the 10th percentile. Only a small part of this association is explained by a lack of green space, and even after adjusting for green space, the increased risk remains approximately 14%.

The association between a greater share of impervious surfaces (built-up areas) and higher diabetes rates, and the association between greener environments and lower diabetes rates (which weakens after adjusting for impervious surfaces), are consistent with findings from numerous studies from Israel and elsewhere regarding the impact of the physical residential environment on chronic morbidity. Studies show that harmful environmental exposures in the built environment (such as air pollution and noise), combined with the influence of the physical environment on lifestyle (such as sedentary behavior), contribute to higher rates of diabetes (Münzel et al., 2021). By contrast, in urban areas characterized by ***high walkability*** (mixed land use, high street connectivity, an aesthetically pleasing environment), ***abundant shade*** (mature trees and urban nature), clean and efficient public transportation that reduces emissions from polluting vehicles and noise and creates a safer and more inviting pedestrian environment, and ***less air pollution from other sources***—diabetes prevalence may be lower, even compared with rural areas.

The principal limitation of this study is its analytic level: ecological instead of individual. This has two possible implications. First, results may be affected by the way that geographic boundaries between the analytic areas are defined. This phenomenon is referred to in the scientific literature as the Modifiable Areal Unit Problem (MAUP). The spatial unit selected for this study, the SGA, describes a residential area whose internal characteristics are generally similar across the area within the SGA and may differ from one area to another, and is a commonly used choice in the scientific literature (Hirsch et al., 2020). Second, although the SGA areas used here are small and we have carefully fit models that include a large body of control variables measured prior to the dependent

variable, it is possible that the results reflect an "aggregation bias"; and that were we able to replicate them on individual-level data, we would find get somewhat different results. In light of this weakness, it is important to conduct studies that bridge the individual and area levels (Subramanian, 2004).

Despite this weakness, the study has two notable strengths. First and foremost, the sample includes the vast majority of residential SGAs in Israel (2,835 of 3,495) and therefore also covers most of Israel's population. Second, and no less important, exposure to green space and the built environment is assessed at high spatial resolution and is accompanied by a wealth of data on additional exposures in the built environment, such as air pollution, street connectivity, and land-use mix. This combination allows for better understanding of the association between the built environment in Israel and diabetes prevalence than is available in any other extant research.

In conclusion, this study shows that spatial variation in diabetes prevalence in Israel is not explained solely by demographic and socioeconomic differences, but is also associated with characteristics of the physical environment of the residential area (SGA). These findings emphasize that urban planning that combines accessible green space with beneficial urban characteristics (walkability, shade, clean public transportation) may help reduce the burden of diabetes in Israel.

Policy options

Beyond the clear health significance of the study findings, they also have substantial economic implications. Diabetes imposes very high costs on the healthcare system — expenditure on a person with diabetes is almost twice as high as expenditure on an insured individual without the disease (Sadeh et al., 2024). Even a moderate reduction in diabetes prevalence or a delay of several years in disease onset could translate into considerable budgetary savings and a reduction in health inequalities. In addition, if there is indeed a correlation between risk factors for diabetes and risk factors for other chronic diseases, including cardiovascular diseases and malignant tumors, as shown, for example, by Wilcox et al. (2024), then any action that reduces diabetes morbidity may also contribute to other health objectives.

As we have shown in this study, green spaces, and particularly a lower share of impervious surfaces, are associated with lower diabetes rates and are therefore not merely a "pleasant aesthetic addition" to residential environments. It is thus essential to give due consideration to the built environment, including green spaces and open areas, in national diabetes prevention policies and urban planning policies. The following are several policy options that may help reduce diabetes prevalence in the population:

1. ***Reducing environments dominated by asphalt and concrete:*** Urban renewal plans and the development of new neighborhoods should include targets for reducing the proportion of impervious surfaces, among other things by converting open parking lots into green or mixed-use spaces, promoting green roofs, and implementing drainage solutions that incorporate greenery and urban nature.

2. ***Increasing greenery within neighborhoods, not only in parks:*** Urban planning should focus not only on increasing the overall share of green space, but also on distributing greenery intelligently and evenly so that most residents can be exposed to it within a short walking distance — through gardens near residential buildings and mature trees along walking routes used by residents in their daily lives. Policies regarding the removal of mature trees as part of urban renewal plans should be reconsidered. This recommendation is particularly important for disadvantaged populations in Israel, especially the Arab population, which suffers from inequality in access to green spaces (OECD, 2025).

3. ***Integrating built-environment indicators into urban planning and public health:*** It is recommended that the Ministry of Health and other relevant government ministries incorporate indicators such as NDVI and the proportion of impervious surfaces into models for monitoring and identifying areas at high risk of diabetes, and use these indicators to prioritize infrastructure investment in disadvantaged neighborhoods.

   More specifically, this study provides an initial framework for establishing thresholds for desirable levels of environments in residential areas in Israel. The European Union and the World Health Organization recommend the "3–30–300" rule—an urban-planning guideline according to which every person should be able to see at least three mature trees from the window

of their home, live in a neighborhood with 30% tree-canopy cover, and have access to a high-quality public green space within 300 meters of their residence (Bertassello et al., 2026). In Israel, urban renewal and evacuation-reconstruction projects tend to increase built-up area at the expense of green and undeveloped spaces. New neighborhoods built in Israel are also characterized by limited green space, concentration of greenery in a specific part of the neighborhood, and a high proportion of impervious surfaces. As this study indicates, such conditions may be harmful to public health. It is therefore recommended that regulations be updated to establish mandatory thresholds for exposure to green and undeveloped environments in evacuation-reconstruction projects and in the planning of new neighborhoods.

4. ***Establishing a health-environment database:*** A health-environment database at the SGA level would make it possible to obtain a clear picture of the areas in which intervention in the physical environment is needed to improve public health, as well as to examine changes in the environment over time and their effects on public health. In addition, access to geocoded individual-level data for environmental research should be ensured. As noted, this study is not the last word on this topic, and further research is needed to provide a deeper understanding of the effects of the physical environment on public health for policy planning purposes. Such research depends on data availability and funding; it is therefore recommended to improve data availability and allocate resources for conducting these studies.

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Appendix

Appendix Table A1. Negative binomial model results for the association between green environments and diabetes rates

Model 1: Environmental variables modeled using methods such as splines

Term	Estimate	se	rr	edf	p
Parametric term					
Intercept	-2.640	0.051	NA	NA	<0.001
SES (continuous, per point, centered at 6; at mean NDVI)	-0.087	0.008	0.917	NA	<0.001
Ethnicity: non-Jewish (versus Jewish)	0.199	0.014	1.220	NA	<0.001
SES quintile					
2	0.113	0.043	1.120	NA	0.008
3	0.123	0.049	1.131	NA	0.011
4	0.089	0.057	1.094	NA	0.119
5	0.146	0.068	1.157	NA	0.032
Locality popultion size					
2	0.073	0.012	1.076	NA	<0.001
3	0.076	0.015	1.079	NA	<0.001
Smooth terms					
NDVI (spline)	NA	NA	NA	2.637	<0.001
NDVI × SES, continuous (spline)	NA	NA	NA	1.747	0.564
Share aged 45+ (spline)	NA	NA	NA	2.978	<0.001
Connectivity (spline)	NA	NA	NA	2.820	0.001
Land-use mix (spline)	NA	NA	NA	1.949	0.265
NO2, per 1 ug/m3 (spline)	NA	NA	NA	3.843	<0.001
PM2.5, per 1 ug/m3 (spline)	NA	NA	NA	2.882	<0.001
s(age at registry) × SES (5 levels)	NA	NA	NA	1.0–2.8	p <0.001–0.450
Model fit					
n (areas)	2673.00				
Adjusted R2	0.97				
Deviance explained (%)	82.44				
REML score	11695.0				
NB theta	47.83				
Pearson dispersion	1.07				
AIC	23241.85				

Table continues

Appendix Table A1 (continued). Negative binomial model results for the association between green environments and diabetes rates

Model 2: Linear modeling of environmental variables

Term	Estimate	se	rr	rr_lo	rr_hi	edf	p
Parametric term							
Intercept	-2.702	0.068	NA	NA	NA	NA	<0.001
NDVI, per 0.1 (linear; at SES 6)	-0.036	0.006	0.965	0.953	0.977	NA	<0.001
SES (continuous, per point, centered at 6; at mean NDVI)	-0.088	0.008	0.916	0.902	0.930	NA	<0.001
Ethnicity: non-Jewish (versus Jewish)	0.196	0.014	1.216	1.183	1.251	NA	<0.001
SES quintile							
2	0.126	0.043	1.134	1.042	1.235	NA	0.004
3	0.135	0.049	1.145	1.040	1.261	NA	0.006
4	0.100	0.058	1.106	0.987	1.239	NA	0.084
5	0.158	0.069	1.171	1.023	1.341	NA	0.022
Locality population size							
2	0.080	0.011	1.083	1.059	1.107	NA	<0.001
3	0.084	0.014	1.087	1.057	1.118	NA	<0.001
Connectivity, per 1 unit (linear)	0.001	0.007	1.001	0.987	1.015	NA	0.892
Land-use mix, per 0.1 (linear)	-0.003	0.003	0.997	0.991	1.002	NA	0.184
NO_2, per 1 ug/m^3 (linear)	0.010	0.001	1.010	1.008	1.011	NA	<0.001
$PM^{2.5}$, per 1 ug/m^3 (linear)	-0.003	0.003	0.997	0.992	1.003	NA	0.334
NDVI × SES: change in NDVI log-RR per 0.1, per SES point	-0.004	0.003	0.996	0.990	1.001	NA	0.120
Smooth terms							
Share aged 45+ (spline)	NA	NA	NA	NA	NA	2.977	<0.001
s(age at registry) × SES (5 levels): edf; p<0.001–0.698	NA	NA	NA	NA	NA	1.0-2.8	p <0.001–0.698
Model fit							
n (areas)	2673.00						
Adjusted R^2	0.97						
Deviance explained (%)	81.68						
REML score	11734.05						
NB theta	45.29						
Pearson dispersion	1.07						
AIC	23328.20						

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points

Appendix Table A2. Negative binomial model results for the association between the built environment and diabetes rates

Model 1: Environmental variables modeled using methods such as splines

Term	Estimate	se	rr	edf	p
Parametric term					
Intercept	-2.640	0.050	NA	NA	<0.001
SES (continuous, per point, centered at 6)	-0.086	0.008	0.917	NA	<0.001
Ethnicity: non-Jewish (versus Jewish)	0.195	0.014	1.215	NA	<0.001
SES quintile					
2	0.119	0.043	1.126	NA	0.005
3	0.136	0.048	1.145	NA	0.005
4	0.095	0.057	1.099	NA	0.097
5	0.153	0.068	1.165	NA	0.024
Locality population size					
2	0.061	0.012	1.063	NA	<0.001
3	0.063	0.014	1.065	NA	<0.001
Smooth terms					
Impervious surface (spline)	NA	NA	NA	2.316	<0.001
Share aged 45+ (spline)	NA	NA	NA	2.982	<0.001
Connectivity (spline)	NA	NA	NA	2.855	<0.001
Land-use mix (spline)	NA	NA	NA	1.661	0.077
NO_2, per 1 ug/m^3 (spline)	NA	NA	NA	3.593	<0.001
$PM_{2.5}$, per 1 ug/m^3 (spline)	NA	NA	NA	2.870	0.001
s(age at registry) × SES (5 levels)	NA	NA	NA	1.0-2.8	p <0.001-0.389
Model fit					
n (areas)	2673.00				
Adjusted R^2	0.97				
Deviance explained (%)	82.58				
REML score	11677.26				
NB theta	48.28				
Pearson dispersion	1.07				
AIC	23217.20				

Table continues

Appendix Table A2 (continued). Negative binomial model results for the association between the built environment and diabetes rates

Model 2: Linear modeling of environmental variables

Term	Estimate	se	rr	rr_lo	rr_hi	edf	p
Parametric term							
Intercept	-2.776	0.067					<0.001
Impervious surface, per 10% of area (linear)	0.024	0.003	1.025	1.019	1.031	NA	<0.001
SES (continuous, per point, centered at 6)	-0.089	0.008	0.915	0.901	0.929	NA	<0.001
Ethnicity: non-Jewish (versus Jewish)	0.194	0.014	1.214	1.181	1.249	NA	<0.001
SES quintile							
2	0.130	0.043	1.139	1.047	1.239	NA	0.002
3	0.149	0.049	1.161	1.055	1.277	NA	0.002
4	0.111	0.058	1.118	0.998	1.251	NA	0.054
5	0.171	0.069	1.186	1.037	1.357	NA	0.013
Locality population size							
2	0.062	0.012	1.064	1.040	1.089	NA	<0.001
3	0.068	0.014	1.070	1.040	1.101	NA	<0.001
Connectivity, per 1 unit (linear)	-0.046	0.010	0.955	0.937	0.973	NA	<0.001
Land-use mix, per 0.1 (linear)	-0.007	0.003	0.993	0.988	0.999	NA	0.013
NO_2, per 1 ug/m^3 (linear)	0.009	0.001	1.009	1.007	1.010	NA	<0.001
$PM^{2.5}$, per 1 ug/m^3 (linear)	-0.002	0.003	0.998	0.993	1.004	NA	0.499
Smooth terms							
Share aged 45+ (spline)	NA	NA	NA	NA	NA	2.978	<0.001
s(age at registry) × SES (5 levels): edf	NA	NA	NA	NA	NA	1.0–2.8	p <0.001–0.747
Model fit							
n (areas)	2673.00						
Adjusted R^2	0.96						
Deviance explained (%)	81.91						
REML score	11713.17						
NB theta	45.98						

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points

Appendix Table A3. Negative binomial model results for the association between built-environment variables and diabetes prevalence, including the standard deviation of the green environment in each statistical area

Term	Estimate	se	rr	edf	p
Parametric term					
Intercept	-2.631	0.051	NA	NA	<0.001
SES (continuous, per point, centered at 6; at mean NDVI)	-0.087	0.008	0.917	NA	<0.001
Ethnicity: non-Jewish (versus Jewish)	0.197	0.014	1.218	NA	<0.001
SES quintile					
2	0.111	0.043	1.117	NA	0.009
3	0.125	0.048	1.133	NA	0.010
4	0.089	0.057	1.093	NA	0.120
5	0.152	0.068	1.164	NA	0.025
Locality population size					
2	0.061	0.012	1.062	NA	<0.001
3	0.063	0.015	1.065	NA	<0.001
Smooth terms					
NDVI (spline)	NA	NA	NA	2.382	0.023
NDVI SD (spline)	NA	NA	NA	2.327	0.338
Impervious surface (spline)	NA	NA	NA	1.970	<0.001
NDVI × SES, continuous (spline)	NA	NA	NA	1.850	0.356
Share aged 45+ (spline)	NA	NA	NA	2.980	<0.001
Connectivity (spline)	NA	NA	NA	2.806	<0.001
Land-use mix (spline)	NA	NA	NA	1.942	0.152
NO_2, per 1 ug/m^3 (spline)	NA	NA	NA	3.727	<0.001
$PM_{2.5}$, per 1 ug/m^3 (spline)	NA	NA	NA	2.879	<0.001
s(age at registry) × SES (5 levels)	NA	NA	NA	1.0–2.7	<0.001–0.365
Model fit					
n (areas)	2673.00				
Adjusted R^2	0.97				
Deviance explained (%)	82.68				
REML score	11686.21				
NB theta	48.56				
Pearson dispersion	1.07				
AIC	23213.12				

Source: Maya Sadeh, Yael Yavin, and Alex Weinreb, Taub Center | Data: Central Bureau of Statistics; Clalit Health Services; Conservation Biology and Biodiversity Lab, Ben-Gurion University of the Negev; Ministry of Environmental Protection; Points