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Association between environmental quality and diabetes in the USA

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ABSTRACT

Aims/Introduction: Caloric excess and physical inactivity fail to fully account for the rise of diabetes prevalence. Individual environmental pollutants can disrupt glucose homeostasis and promote metabolic dysfunction. However, the impact of cumulative exposures on diabetes risk is unknown.

Materials and Methods: The Environmental Quality Index, a county-level index composed of five domains, was developed to capture the multifactorial ambient environmental exposures. The Environmental Quality Index was linked to county-level annual age-adjusted population-based estimates of diabetes prevalence rates. Prevalence differences (PD, annual difference per 100,000 persons) and 95% confidence intervals (CI) were estimated using random intercept mixed effects linear regression models. Associations were assessed for overall environmental quality and domain-specific indices, and all analyses were stratified by four rural-urban strata.

Results: Comparing counties in the highest quintile/poorest environmental quality to those in the lowest quintile/best environmental quality, counties with poor environmental quality demonstrated lower total diabetes prevalence rates. Associations varied by rural–urban strata; overall better environmental quality was associated with lower total diabetes prevalence rates in the less urbanized and thinly populated strata. When considering all counties, good sociodemographic environments were associated with lower total diabetes prevalence rates (prevalence difference 2.77, 95% confidence interval 2.71–2.83), suggesting that counties with poor sociodemographic environments have an annual prevalence rate 2.77 per 100,000 persons higher than counties with good sociodemographic environments.

Conclusions: Increasing attention has focused on environmental exposures as contributors to diabetes pathogenesis, and the present findings suggest that comprehensive approaches to diabetes prevention must include interventions to improve environmental quality.

INTRODUCTION

The prevalence of diabetes has increased dramatically over the past several decades, with the disease now afflicting >30 million people in the USA, and an additional 84 million individuals with prediabetes at risk of progressing to diabetes in the coming years[1]. As the leading cause of adult blindness, kidney failure and non-traumatic amputations, as well as a potent contributor to cardiovascular disease, diabetes exerts a tremendous toll on individual morbidity and mortality[1]. Furthermore, this generates a significant societal burden, as the annual economic costs associated with diagnosed diabetes exceed $327 billion in the USA alone, with significant deterioration in the quality of life for affected individuals and their families[2].

Despite abundant evidence that caloric excess and physical inactivity superimposed on a susceptible genetic background

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drive diabetes pathogenesis, these factors alone fail to fully account for the rapid rise of diabetes prevalence both nationally and internationally[3]. As such, increasing attention has turned to additional contributors to diabetes pathogenesis, including the impact of exposure to environmental pollutants. In fact, diabetes rates in the USA are tightly correlated with the production and environmental distribution of synthetic chemicals[4]. Studies have shown that various pollutants can disrupt glucose homeostasis and promote metabolic dysfunction[4–8]. These diabetogenic agents span a broad range of chemical classes and routes of exposure. Importantly, levels and intentional use of these toxicants can vary across communities and regions.

In addition, diabetes prevalence shows regional variation across the USA.[9] Variations in the use of and exposure to various chemicals might contribute to the geographic variability of diabetes prevalence. Chemicals that have been associated with metabolic dysfunction include compounds found in the home (e.g., flame retardants, bisphenol A and phthalates[10–14]), used occupationally (e.g., pesticides[15,16]), and that arise from local industrial practices and urbanization (e.g., air pollutants[17]). Additionally, environmental pollutants associated with diabetes have been shown to disproportionately affect minority communities[18]. Thus, based on differences in the national distribution of chemical-intensive practices and other regional factors, toxicant exposures might contribute to geographical variation in diabetes rates.

Although in rare cases isolated exposure to a single chemical is sufficient to drive diabetes development[19], it is much more likely that multiple exposures, coupled with additional risk factors, are required to drive diabetes pathogenesis[20]. Epidemiological research traditionally focuses on single environmental exposures. The burden of cumulative, or simultaneous, environmental exposures on diabetes risk has not been systematically examined. To capture multifactorial ambient environmental exposures, the Environmental Quality Index (EQI) was developed. The publicly available EQI is a county-level measure of cumulative ambient environmental exposures for the USA for the period 2000–2005[21]. The index was constructed to provide overall EQI, as well as domain-specific indices for all counties in the USA. Accounting for the proposed 5–10-year lag period between diabetes onset and diagnosis[22–24], we used the EQI to assess the burden of cumulative environmental exposures on diabetes prevalence in the USA. We examined county-level diabetes prevalence for 2004–2012 in association with the EQI. We also considered associations with domain-specific indices to assess which domains, if any, drive associations with diabetes prevalence. In addition, it is known that factors that influence environmental quality vary in rural and urban areas; therefore, all analyses were also stratified by rural–urban status.

METHODS

Study population

Population-based county-level estimates for diagnosed (DDP), undiagnosed (UDP) and total diabetes prevalence (TDP) were downloaded from the Institute for Health Metrics and Evaluation for the years 2004–2012[25]. Prevalence estimates were calculated using a two-stage approach. The first stage used National Health and Nutrition Examination Survey data to predict high fasting plasma glucose (FPG) levels (≥126 mg/dL) and/or hemoglobin A1c (HbA1c) levels (≥6.5% [48 mmol/mol]) based on self-reported demographic and behavioral characteristics[26]. This model was then applied to Behavioral Risk Factor Surveillance System (BRFSS) data to impute high FPG and/or HbA1c status for each BRFSS respondent[26]. The second stage used the imputed BRFSS data to fit a series of small area models, which were used to predict the county-level prevalence of each of the diabetes-related outcomes[26]. Diagnosed diabetes was defined as the proportion of adults (aged ≥20 years) who reported a previous diabetes diagnosis, represented as an age-standardized prevalence percentage. Undiagnosed diabetes was defined as the proportion of adults (aged ≥20 years) who had a high FPG or HbA1c, but did not report a previous diagnosis of diabetes. Total diabetes was defined as the proportion of adults (aged ≥20 years) who reported a previous diabetes diagnosis and/or had a high FPG/HbA1c. The age-standardized diabetes prevalence (%) was used as the outcome.

Exposure data: The EQI

The EQI was used as an exposure metric as an indicator of cumulative environmental exposures at the county-level representing the period 2000–2005. The EQI includes variables representing each of five environmental domains: air, water, land, built environment and sociodemographic. A complete description of the datasets used in the EQI is provided in Lobdell *et al*[27]., and methods used for index construction are described by Messer *et al*[28]. Briefly, domain-specific indices (air index, water index etc.) were created by retaining the first component of a principal components analysis that included all of the domain-specific variables. Examples of variables included in each domain are provided in Table 1. The EQI was then created by retaining the first component of a principal components analysis that combined the domain-specific indices. Recognizing that environments differ across the rural–urban continuum, the EQI and domain-specific indices construction were stratified by rural–urban continuum codes (RUCC)[29]. We utilized four categories for which RUCC1 represents metropolitan urbanized; RUCC2 non-metro urbanized; RUCC3 less urbanized; and RUCC4 thinly populated, which have been used in previous health analyses[30–32]. Finally, we have six non-stratified indices (one overall EQI and five domain-specific indices) and six corresponding indices for each of the four RUCC strata. This allows for assessment of cumulative environmental exposure, domain-specific drivers and rural–urban variations. For the domain-specific analysis, we valence corrected the domain-specific indices to ensure that the directionality of the variables was consistent with higher values suggesting poorer quality (more pollution).

The Institute for Health Metrics and Evaluation diabetes prevalence data was merged with the EQI data by county name, state and county Federal Information Processing

Table 1 | Select variables that represent each domain of the Environmental Quality Index

Domain	Example variables
Air	Criteria and hazardous air pollutant concentrations, particulate matter concentration, sulfur dioxide, chlorine
Water	Contaminant concentrations, drought status, number of discharge permits, water withdrawals for industrial uses
Land	Percentage of land in wheat crops, insecticide-treated crops, count of superfund sites and brownfields, mean arsenic from sediment samples
Sociodemographic	Median household income, percentage of individuals with less than a high school education, violent crime rate, property crime rate
Built	Density of fast food restaurants, percentage of all roadways that are highways, density of fatal accidents, density of public housing units

Standards code. There were spelling differences between the Institute for Health Metrics and Evaluation and the EQI data; however, once the differences were fixed, just seven counties (four in Alaska, one in South Dakota and two in Virginia) were excluded from the final analysis (n = 3,134 counties), as they did not have corresponding EQI data available.

Covariates

County-level data on obesity and leisure time physical inactivity for 2004–2012 were downloaded from the Centers for Disease Control and Prevention[9] to use as covariates in analyses. These values are estimated from the BRFSS data using Bayesian methods to statistically model estimates utilizing data from surrounding counties to strengthen estimates for individual counties[33].

Statistical analysis

We used a random intercept mixed effect linear model, with state as a fixed effect, to estimate the fixed effects of EQI quintiles and environmental domain-specific quintiles on diabetes prevalence annually. We carried out analyses using quintiles, which allows for more meaningful interpretation (between areas of good [1], moderate [3] and poor [5] environmental quality, for instance). We considered three diabetes outcomes: DDP, UDP and TDP. In addition, we adjusted for county-level covariates of obesity prevalence and leisure time physical inactivity prevalence.

Results are reported as both overall and individual year annual prevalence differences (PD) with the 95% confidence intervals (CI) comparing the highest quintile/worst environmental quality with the lowest quintile/best environmental quality for all three outcomes, diagnosed, undiagnosed and total diabetes. Overall PDs are representative of the entire period of interest, 2004–2012, whereas individual annual PDs are representative of a single year (2004, 2005, 2006, etc.). All analyses were stratified by four rural–urban continuum codes to assess associations by urbanicity. Analyses were carried out using R (R Foundation for Statistical Computing, Vienna, Austria) and SAS (v9.4; SAS Institute, Cary, NC, USA) statistical software. Internal review board approval was not required, as the data are all secondary and aggregated at the county-level.

RESULTS

Population description

There were a total of 3,134 counties represented in the analysis. Of these, 34.7% (n = 1,088) were metropolitan-urbanized (RUCC1), 10.3% (323) were non-metropolitan urbanized (RUCC2), 33.7% (1,056) were less-urbanized (RUCC3) and 21.3% (667) were thinly populated (RUCC4). This mirrors the RUCC distribution of all USA counties, which is also 34% RUCC1, 10% RUCC2, 34% RUCC3 and 21% RUCC4. The average annual county-level diagnosed, undiagnosed and total diabetes prevalence rates were 9.61 per 100,000 population (standard deviation 2.09), 3.85 per 100,000 population (standard deviation 0.42) and 13.58 per 100,000 population (standard deviation 2.44), respectively. The mean and standard deviations of DDP, UDP and TDP varied across rural–urban strata (Table 2).

Table 2 | County-level mean and standard deviation for all years 2004–2012 for all counties and stratified by rural-urban status

Outcome	All counties	Metropolitan-urbanized (RUCC1)	Non-metropolitan-urbanized (RUCC2)	Less urbanized (RUCC3)	Thinly populated (RUCC4)
Diagnosed diabetes	9.61 ± 2.09	9.50 ± 1.83	9.74 ± 2.04	9.86 ± 2.21	9.33 ± 2.23
Undiagnosed diabetes	3.85 ± 0.42	3.90 ± 0.38	3.93 ± 0.42	4.07 ± 0.47	3.98 ± 0.46
Total diabetes	13.58 ± 2.44	13.40 ± 2.14	13.67 ± 2.40	13.92 ± 2.59	13.31 ± 2.58

RUCC, rural–urban continuum code; RUCC1, metropolitan-urbanized counties; RUCC2, Non-metropolitan-urbanized counties; RUCC3, less-urbanized counties; RUCC4, thinly populated counties.

Overall, poor cumulative environmental quality, controlling for obesity and leisure time physical inactivity, was associated with lower TDP rates for all counties (PD –1.36, 95% CI –1.43, –1.28, comparing counties with the worst environmental quality with counties with the best environmental quality; Figure 1; Table S1). Similarly, lower DDP and UDP rates were associated with poor cumulative environmental quality (Figures S1,S2). The results with cumulative environmental quality and TDP varied by rural–urban status (summarized in Table 3). In the metropolitan-urbanized strata, the association was null (PD 0.07, 95% CI –0.03, 0.17); however, in the less urbanized (PD 2.58, 95% CI 2.46, 2.71) and thinly populated (PD 2.88, 95% CI 2.74, 3.01) strata, poor cumulative environmental quality was associated with higher TDP rates. Similarly, UDP and DDP showed varying results with cumulative environmental quality in the metropolitan-urbanized and non-metro urbanized strata, but poor cumulative environmental quality was associated with higher UDP and DDP rates in the less urbanized and thinly populated strata (Figures S3,S4).

For all counties, associations with TDP varied across domains (summarized in Table 3); water and land showed inverse associations; in contrast, air, sociodemographic, and built environment showed positive associations. The sociodemographic domain showed the strongest association with TDP (PD 2.77, 95% CI 2.71, 2.83, comparing counties with the worst sociodemographic quality with counties with the best sociodemographic quality; Figure 1; Table S1). When considering all counties, higher DDP rates were associated with poorer air quality (PD 0.44, 95% CI 0.38, 0.51), poorer sociodemographic factors (PD 2.24, 95% CI 2.19, 2.29) and worse built environment factors (PD 0.14, 95% CI 0.10, 0.19; Figure S1), and higher UDP rates were only associated with poorer

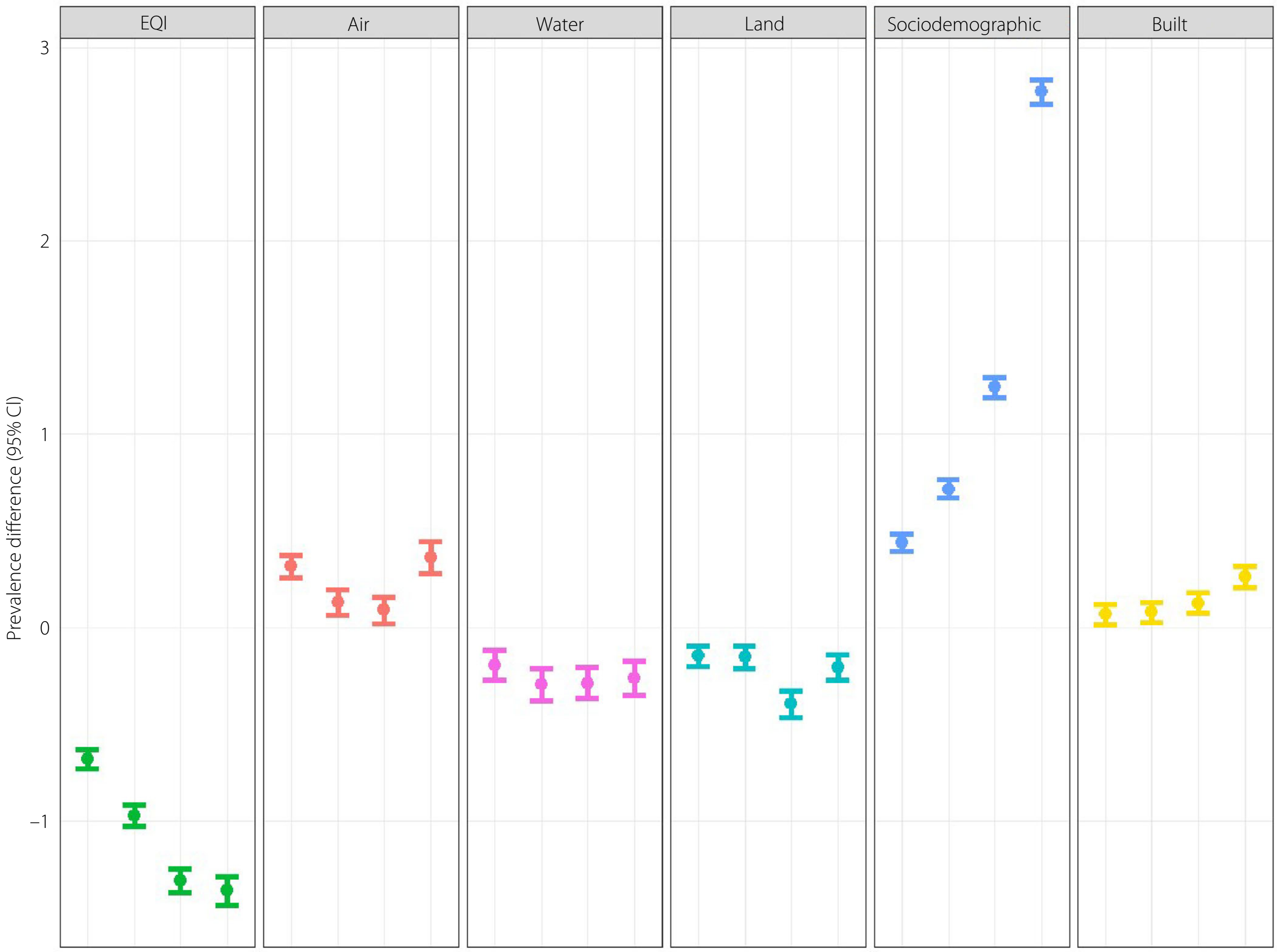

Figure 1 | Total diabetes prevalence differences with 95% confidence intervals (CI) for all counties by quintiles, with the lowest quintile (quintile 1) or best environmental quality as the reference, with worsening environmental quality increasing left to right for Environmental Quality Index (EQI) and domain-specific indices, controlling for obesity prevalence and leisure time physical inactivity prevalence.

Table 3 | Summary of results for total diabetes prevalence for overall environmental quality and by domains for all counties and by rural/urban strata

Poor	Is associated with __ rates of TDP	For
Overall environmental quality (EQI)	↓	All counties
	–	RUCC1
	↓	RUCC2
	↑	RUCC3, RUCC4
Air quality	–	All counties
	↑	RUCC1
	–	RUCC2
	↓	RUCC3, RUCC4
Water quality	–	All counties
	–	RUCC1, RUCC2, RUCC3, RUCC4
Land quality	–	All counties
	–	RUCC1, RUCC2, RUCC3, RUCC4
Sociodemographic environment	↑	All counties
	↑	RUCC1, RUCC2, RUCC3, RUCC4
Built environment	–	All counties
	↓	RUCC1
	↑	RUCC2, RUCC3, RUCC4

EQI, Environmental Quality Index; RUCC, rural–urban continuum code; RUCC1, metropolitan-urbanized counties; RUCC2, Non-metropolitan-urbanized counties; RUCC3, less-urbanized counties; RUCC4, thinly populated counties; TDP, total diabetes prevalence.

sociodemographic factors (PD 0.53, 95% CI 0.52, 0.55) and worse built environment factors (PD 0.12, 95% CI 0.11, 0.13; Figure S2).

Similar to overall EQI, associations with domain-specific indices varied by rural–urban status (Figure 2; Table S2). Higher TDP rates were associated with poor air quality (PD 0.71, 95% CI 0.62, 0.79) only in the metropolitan-urbanized strata (Figure 2), and associations with all other domains varied for the metropolitan-urbanized stratum. Higher TDP rates also showed associations with poorer sociodemographic quality in all strata with the strongest association in the thinly populated strata (PD 3.57, 95% CI 3.46, 3.68). Similar to TDP, higher DDP rates were associated with poorer sociodemographic quality in all strata, with the strongest association in the thinly populated strata (PD 2.89, 95% CI 2.80, 2.98; Figure S3). Overall, UDP showed weaker associations across all domains, and all rural–urban strata compared with TDP and DDP (Figure S4). For UDP, there were positive associations in the sociodemographic domain, except in non-metropolitan-urbanized strata, but the association was weaker than those shown in TDP and DDP.

Analyses for individual years showed similar patterns to results for the entire time period for overall EQI and all three outcomes: TDP (Figure 3; Table S3), DDP (Figure S5) and UDP (Figure S6). This was also true for analyses by individual domains (results not shown). Again, poorer sociodemographic quality was associated with higher rates for all three outcomes. For all counties, annual associations between overall EQI and TDP, DDP and UDP followed a similar pattern as estimates for the overall time period; diabetes prevalence decreased with worsening environmental quality. Annual estimates for individual domains and all three outcomes varied; however, the patterns were similar to those seen for the overall time period. The air, water, land and built environment domains showed slightly more positive associations, but PD estimates for all years were close to null. Annual estimates for the sociodemographic domain and all three outcomes showed positive associations for all years.

DISCUSSION

Increasing evidence implicates environmental toxicants in the pathogenesis of metabolic disease; however, the impact of cumulative exposures on diabetes risk remains poorly understood. To address this important data gap, we used a comprehensive measure of environmental quality derived largely from publicly available datasets that quantifies environmental risk at the county-level. Using this index, we found that diabetes prevalence was not associated with overall, cumulative, environmental quality for all counties in the USA, but associations varied for specific domains and by rural–urban status. Overall environmental quality was strongly associated with total diabetes prevalence in the less urbanized and thinly populated strata. For all counties, the strongest association was seen in the sociodemographic domain, which showed an increased total diabetes prevalence of 2.77 in counties with poor sociodemographic quality compared with counties with the best sociodemographic quality. Additionally, both diagnosed and undiagnosed diabetes prevalence were strongly associated with the sociodemographic domain when considering all counties. Associations between total diabetes prevalence and sociodemographic domain varied by rural–urban strata, with the strongest associations shown in the thinly populated strata.

The present findings suggesting that poor air quality is associated with increased diabetes risk in urban areas are consistent with previous literature examining associations between single air pollutants and diabetes[34–41]. Consistent with data showing that changes in air quality can rapidly increase insulin resistance[41–43], counseling patients to avoid high levels of air pollutants might be advisable. This includes avoiding exercise near busy roads or during peak traffic periods, as well as choosing efficient commuting routes that minimize time spent in heavy traffic. Additionally, in accordance with data showing that diabetes risk is inversely associated with greenery[44,45], encouraging the extensive planting of trees, shrubs and other plants has the potential to improve air quality through the plants' capacity to filter air pollutants.

The present findings also showed varying associations by rural–urban status. We found strong associations between total diabetes prevalence and the sociodemographic domain for all

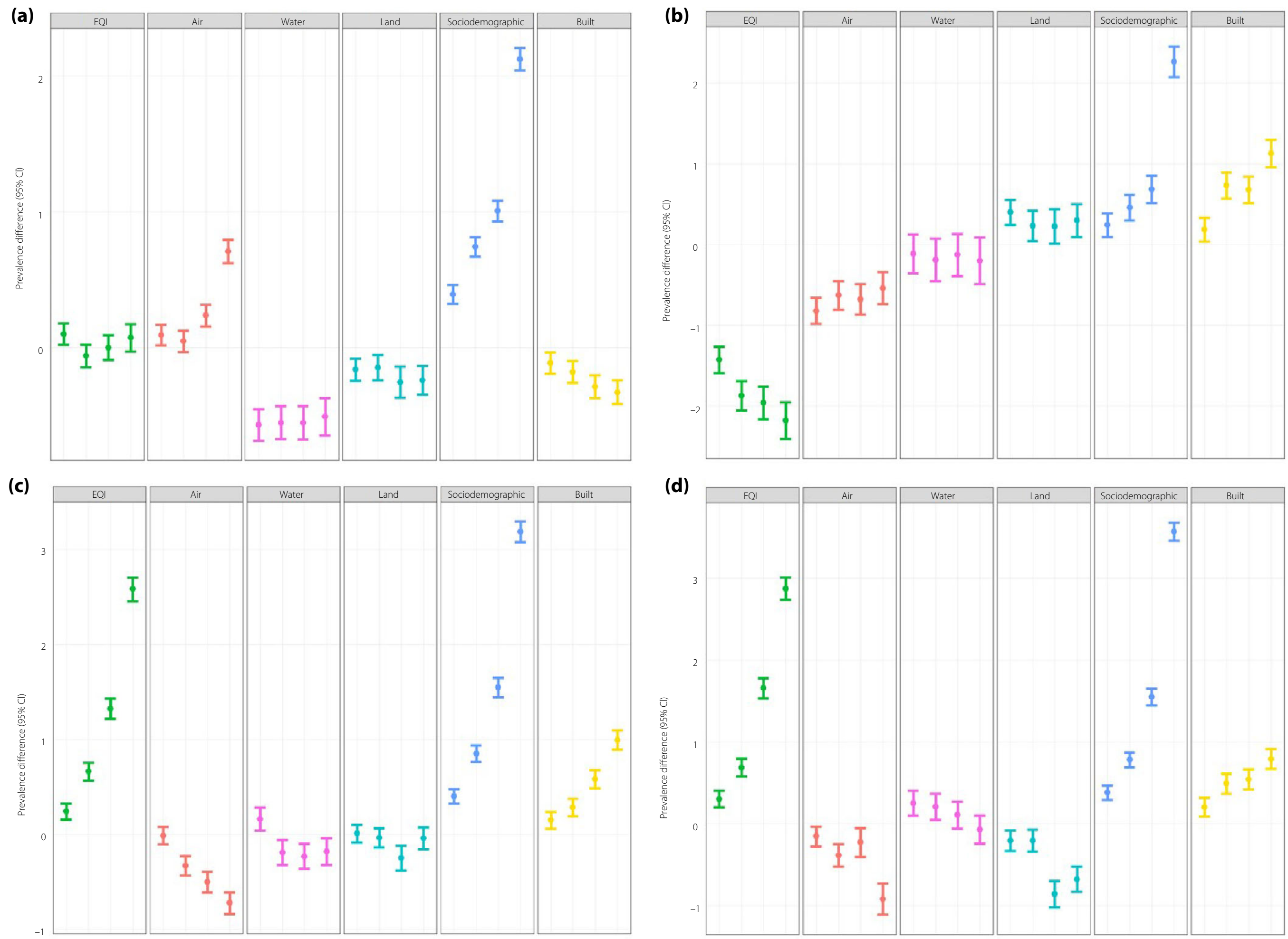

Figure 2 | Total diabetes prevalence differences with 95% confidence intervals (CI) for all counties by quintiles, with the lowest quintile (quintile 1) or best environmental quality as the reference, with worsening environmental quality increasing left to right for Environmental Quality Index (EQI) and domain-specific indices, controlling for obesity prevalence and leisure time physical inactivity prevalence by rural–urban strata. (a) Metropolitan Urbanized (rural–urban continuum code 1 [RUCC1]). (b) Non-Metropolitan-Urbanized (RUCC2). (c) Less Urbanized (RUCC3). (d) Thinly Populated (RUCC4).

counties and in all rural–urban strata. The metropolitan-urbanized strata counties with poor sociodemographic environment showed a 1.73% increase in annual diagnosed diabetes prevalence compared with counties with the best sociodemographic environment; this translates to an estimated increase of 13.84% over the 8-year study period. The thinly populated counties showed a 2.89% increase in annual diagnosed diabetes, which is an estimated increase of 23.12% over the 8-year study period. Previous studies have shown that drivers of diabetes risk vary in rural and urban areas[46–48]. Healthcare access and food insecurity have been associated with increased rates of diabetes[47,49]. Additionally, poverty has been shown to be associated with diabetes; however, this association is modified by geographic location[47]. We showed increasingly stronger associations with the sociodemographic domain from the metropolitan-urbanized strata to the thinly populated strata, suggesting that sociodemographic drivers of diabetes risk might differ between rural and urban regions. We also showed positive associations with the built environment domain in all strata except the metropolitan-urbanized strata; however, the majority of research on built environment factors focuses on urban areas.

Although environmental health research has utilized indices to represent multiple variables with a single quantitative measure, the EQI is the first to assess exposures across multiple domains of exposure. Indices have been developed to represent the built and social environments[50,51], and to consider mixtures of air pollutants[52]. However, environmental exposures occur simultaneously and work through multiple mechanisms to result in diabetes. This is the first study, of which we are aware, to utilize an index of environmental quality to assess the

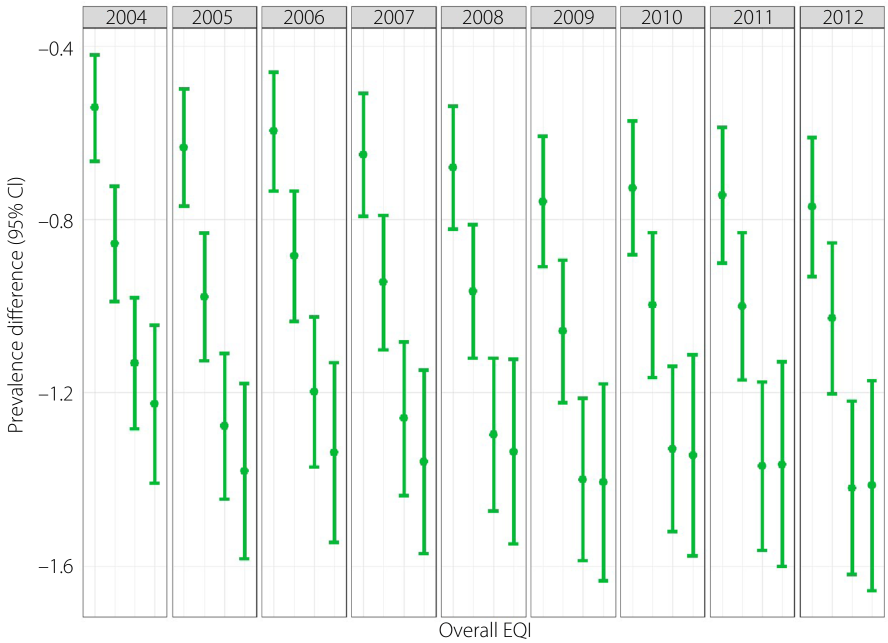

Figure 3 | Annual estimates, 2004–2012, of total diabetes prevalence differences with 95% confidence intervals (CI) for all counties by quintiles, with the lowest quintile (quintile 1) or best environmental quality as the reference, with worsening environmental quality increasing left to right for Environmental Quality Index, controlling for obesity prevalence and leisure time physical inactivity prevalence.

burden of cumulative environmental exposures on diabetes prevalence.

The EQI is a metric of cumulative environmental exposures that was developed utilizing publicly available data. However, environmental data are typically collected for administrative and regulatory purposes, and therefore might not provide the spatial and/or temporal coverage to properly assess health outcomes[53]. For example, several of the pollutants captured in the water and land domains are associated with diabetes rates[54–58], yet we did not see positive associations. This might be due to the data quality for those domains, which is less robust than for other domains, as it is primarily collected for regulatory purposes[53]. Additionally, environmental data better represent urban areas compared with suburban and rural areas. Several of the factors included in the exposure metric, as well as the outcome of county-level diabetes rates, show spatial relationships. We did not account for any spatial associations in our analyses. These factors might show clustering effects that should be considered and accounted for in future analyses.

The EQI is an ecological exposure metric that is both a strength and limitation of the present study. The EQI represents the period 2000–2005, and reflects exposures occurring during and before the diabetes prevalence considered in this analysis. However, the lag period for development of diabetes due to environmental exposures is not known and might not be sufficient. Additionally, the ecological nature of this analysis does not allow us to account for known individual-level behaviors that are strongly associated with diabetes, such as diet and exercise. We control for county-level rates of obesity and physical inactivity that are strongly associated with and on the causal pathway to diabetes. The inclusion of these factors might bias the present results to the null, suggesting that they are stronger drivers of diabetes risk than environmental exposures. It is also important to note that several environmental pollutants have been linked to obesity risk[4], which in turn drives diabetes risk; therefore, adjustment for obesity rates might underestimate associations between environmental exposures and diabetes prevalence. We did consider analyses without adjusting for rates of obesity and physical inactivity, and they showed the same trends with slightly higher estimates. Importantly, as an ecological study, these analyses did not account for individual-level exposures. As human behavior can dramatically modify exposure to various environmental toxicants linked to diabetes risk (e.g., bisphenol A, phthalates, pesticides etc.)[59–61], the present analysis likely underrepresents the contribution of environmental toxicants to diabetes risk. Further work is required to illuminate the extent of human exposure to diabetes-promoting toxicants in the population.

Despite these limitations, the application of broad ecological exposure metrics, such as the EQI, provides new insights into the impact of cumulative environmental exposures. The EQI considers hundreds of environmental exposures simultaneously across multiple environmental domains, including the sociodemographic environment, which is often neglected when considering environmental exposures. In addition, we were able to leverage publicly available exposure and outcome data to assess relationships between environmental quality and diabetes prevalence on a national level. These data provide intriguing insights that should prompt targeted investigations into how socioeconomic drivers of diabetes vary across the urban–rural continuum in order to better tailor intervention strategies to specific communities. In addition, these analyses provide striking support for the connection between poor air quality and diabetes risk, particularly in urban areas.

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DISCLOSURE

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1 | Total diabetes prevalence differences with 95% confidence intervals for all counties by quintiles of Environmental Quality Index and domain-specific indices, controlling for obesity prevalence and leisure time physical inactivity prevalence.

Table S2 | Total diabetes prevalence differences with 95% confidence intervals by quintiles of Environmental Quality Index and domain-specific indices, controlling for obesity prevalence and leisure time physical inactivity prevalence by rural–urban strata (Metropolitan Urbanized [RUCC1], Non-Metropolitan Urbanized [RUCC2], Less Urbanized [RUCC3], Thinly Populated [RUCC4]).

Table S3 | Annual estimates, 2004–2012, of total diabetes prevalence differences with 95% confidence intervals for all counties by quintiles of Environmental Quality Index, controlling for obesity prevalence and leisure time physical inactivity prevalence.

Figure S1 | Diagnosed diabetes prevalence differences with 95% confidence intervals for all counties by quintiles (quintile 1, highest quality [reference], to quintile 5, poor quality) of Environmental Quality Index and domain-specific indices, controlling for obesity prevalence and leisure time physical inactivity prevalence.

Figure S2 | Undiagnosed diabetes prevalence differences with 95% confidence intervals for all counties by quintiles (quintile 1, highest quality [reference], to quintile 5, poor quality) of Environmental Quality Index and domain-specific indices, controlling for obesity prevalence and leisure time physical inactivity prevalence.

Figure S3 | Diagnosed diabetes prevalence differences with 95% confidence intervals for all counties by quintiles (quintile 1, highest quality [reference], to quintile 5, poor quality) of Environmental Quality Index and domain-specific indices, controlling for obesity prevalence and leisure time physical inactivity prevalence, by rural–urban strata (A – Metropolitan Urbanized [RUCC1], B – Non-Metropolitan Urbanized [RUCC2], C – Less Urbanized [RUCC3], D – Thinly Populated [RUCC4]).

Figure S4 | Undiagnosed diabetes prevalence differences with 95% confidence intervals for all counties by quintiles (quintile1, highest quality [reference], to quintile 5, poor quality) of Environmental Quality Index and domain-specific indices, controlling for obesity prevalence and leisure time physical inactivity prevalence, by rural-urban strata (A – Metropolitan Urbanized [RUCC1], B – Non-Metropolitan Urbanized [RUCC2], C – Less Urbanized [RUCC3], D – Thinly Populated [RUCC4]).

Figure S5 | Annual estimates, 2004–2012, of diagnosed diabetes prevalence differences with 95% confidence intervals for all counties by quintiles (quintile 1, highest quality (reference), to quintile 5, poor quality) of Environmental Quality Index, controlling for obesity prevalence and leisure time physical inactivity prevalence.

Figure S6 | Annual estimates, 2004–2012, of undiagnosed diabetes prevalence differences with 95% confidence intervals for all counties by quintiles (quintile 1, highest quality [reference], to quintile 5, poor quality) of Environmental Quality Index, controlling for obesity prevalence and leisure time physical inactivity prevalence.