Original Research Article

Environmental Epidemiology

OPEN

Latent growth trajectories of county-level diabetes prevalence in the United States, 2004–2017, and associations with overall environmental quality

Tara P. McAlexander[a], Jyotsna S. Jagai[b,c], Leslie A. McClure[a]

Background: The prevalence of type 2 diabetes (T2D) has increased in the United States, and recent studies suggest that environmental factors contribute to T2D risk. We sought to understand if environmental factors were associated with the rate and magnitude of increase in diabetes prevalence at the county level.
Methods: We obtained age-adjusted diabetes prevalence estimates from the CDC for 3,137 US counties from 2004 to 2017. We applied latent growth mixture models to these data to identify classes of counties with similar trends in diabetes prevalence over time, stratified by Rural Urban Continuum Codes (RUCC). We then compared mean values of the US EPA Environmental Quality Index (EQI) 2006–2010, overall and for each of the five domain indices (air, water, land, sociodemographic, and built), with RUCC-specific latent class to examine associations of environmental factors and class of diabetes prevalence trajectory.
Results: Overall diabetes prevalence trends between 2004 and 2017 were similar across all RUCC strata. We identified two classes among metropolitan urbanized (RUCC 1) counties; four classes among non-metro urbanized (RUCC 2) counties; and three classes among less urbanized (RUCC 3) and thinly populated (RUCC 4) counties. Associations with overall EQI values and class of diabetes prevalence trends differed by RUCC strata, with the clearest association between poor air EQI and steeper increases in diabetes prevalence among rural counties (RUCC 3 and 4).
Conclusions: Similarities in county-level diabetes prevalence trends between 2004 and 2017 were identified for each RUCC strata, although associations with environmental factors varied by rurality.

Keywords: Diabetes; Environmental quality; Rurality

Introduction

Diabetes prevalence, particularly the prevalence of type 2 diabetes (T2D), has increased steadily in the past 20 years in the United States. Median age-adjusted county-level prevalence of diagnosed diabetes among adults aged 20 years or older increased from 7.8% in 2004 to 13.1% in 2016,[1] and diabetes prevalence in the United States has increased within several population subgroups (including age, sex, race/ethnicity, education level, and income level).[2] These increases are also evident across the globe.[3] Although there are diagnostic and treatment changes that could account for increases in diabetes diagnoses (such as improved detection, decreased mortality), evidence suggests that individual risk factors (including poor diet, smoking, and physical inactivity) and contextual risk factors have contributed to increases in diabetes over time.[4,5]

Among these contextual factors, environmental characteristics such as walkability, air pollution, noise, food and physical activity environments, and green spaces have been associated with T2D risk.[6] One challenge in measuring associations between environmental characteristics and diabetes outcomes is that several of these environmental characteristics cluster together in communities and neighborhoods; it is therefore difficult to

What this study adds

We examine United States county-level diabetes prevalence from 2004 to 2017 using latent growth mixture models, identifying counties with similar diabetes prevalence trajectories over a 14-year period. We then compare latent classes of counties with measures of domain-specific (i.e., air, water, land, sociodemographic, and built) and overall environmental quality, seeking to understand what, if any, environmental factors and conditions might be associated with changes in county-level diabetes prevalence over this time. Associations with overall and domain-specific environmental quality differed by Rural Urban Continuum Codes (RUCC) strata, suggesting that the association between environmental conditions and county-level diabetes prevalence trajectories is modified by rurality.

[a]Department of Epidemiology and Biostatistics, Dornsife School of Public Health, Drexel University, Philadelphia, Pennsylvania; [b]Department of Environmental and Occupational Health Sciences, University of Illinois Chicago, Chicago, Illinois; and [c]Department of Obstetrics and Gynecology, University of Chicago, Chicago, Illinois.

The authors declare that they have no conflicts of interest with regard to the content of this report.

Funding support provided by the Diabetes LEAD Network through CDC cooperative agreement U01DP006293 (Drexel University).

Data used for this analysis are publicly available. County-level diabetes prevalence data are available for download via the CDC: https://gis.cdc.gov/grasp/diabetes/diabetesatlas.html. County-level Environmental Quality Index (EQI) data are available for download via the US EPA: https://www.epa.gov/healthresearch/environmental-quality-index-eqi. R code for replicating this analysis is available upon request by Tara P. McAlexander, tpm58@drexel.edu.

**Corresponding Author. Address: Department of Epidemiology and Biostatistics, Dornsife School of Public Health, Drexel Univeristy, 3215 Market Street, Room 521, Philadelphia, PA 19104. E-mail: tpm58@drexel.edu (T.P. McAlexander).*

Copyright © 2022 The Authors. Published by Wolters Kluwer Health, Inc. on behalf of The Environmental Epidemiology. All rights reserved. This is an open-access article distributed under the terms of the Creative Commons Attribution-Non Commercial-No Derivatives License 4.0 (CCBY-NC-ND), where it is permissible to download and share the work provided it is properly cited. The work cannot be changed in any way or used commercially without permission from the journal.

Environmental Epidemiology (2022) 6:e218

Received: 1 February 2022; Accepted 14 June 2022

Published online 29 June 2022

DOI: 10.1097/EE9.0000000000000218

isolate competing causal environmental risk factors that operate at the contextual level.[7] Fortunately, substantial efforts have been dedicated to characterizing environmental burden in communities.[8] The US Environmental Protection Agency (EPA) Environmental Quality Index (EQI) characterizes environmental burden at the county level among five domains (air, water, land, sociodemographic, built environment), stratified by four Rural-Urban Continuum Codes (RUCC) to account for level of urbanicity at the county level.[8,9]

Recently, Jagai et al[10] have found higher EQI scores, indicating worse environmental quality, between 2000 and 2005 were associated with greater annual county-level prevalence of diabetes (2004–2012) among more rural RUCC strata, although findings were null or in the opposite direction in more urban RUCC strata. These findings are consistent with a growing body of environmental epidemiology literature suggesting that environmental factors contribute to T2D risk.[6] However, the temporality of this relationship is not well described at a population level, which might explain some of the conflicting results by RUCC strata in the Jagai et al[10] analysis. Given the persistent increases in diabetes prevalence and the continuing changes in our environment, we evaluated whether EQI scores, including domain-specific EQI (e.g., air, land, water, built environment, and sociodemographic domains), were associated with the trajectories of county-level prevalence measures over time. We hypothesized that counties with higher overall EQI scores, and thus poor environmental quality, would have steeper increases in diabetes prevalence estimates compared to counties with lower EQI scores; that associations would be strongest for the air and sociodemographic EQI; and that associations would vary by RUCC strata.

Methods

We obtained age-adjusted estimates of diabetes prevalence among adults (≥18 years of age) from the Centers for Disease Control and Prevention (CDC) for all counties in the contiguous US for 2004–2017.[11] These age-adjusted prevalence estimates were based on the CDC's National Health Interview Survey (NHIS) and modeled to estimate county-level prevalence levels for each year.[12] To first understand county-level changes in diabetes prevalence over this time period, we plotted diabetes prevalence trajectories from 50 randomly selected counties from each of the US Department of Agriculture's Rural Urban Continuum Codes (RUCC) classifications[13]: RUCC1 (metropolitan urbanized), RUCC2 (non-metro urbanized), RUCC3 (less urbanized), and RUCC4 (thinly populated). Fifty counties were randomly selected from the larger sample to facilitate interpretation. These RUCC classifications distinguish metropolitan and non-metropolitan counties based on population size and adjacency to metropolitan counties.[13]

We obtained estimates of the county-level EQI from the US EPA spanning 2006–2010, reflecting five domains: air, water, land, sociodemographics, and built environment.[9] The EQI were calculated separately by strata of RUCC classification and are, thus, not comparable across RUCC strata. Details about the derivation of the EQI, including the sources for each variable included in the measure, can be found elsewhere.[8] In brief, multiple national data sources were used in a principal component analysis (PCA) derived domain-specific EQIs, which in turn are used in a PCA to derive the overall EQI. The EQI utilizes ambient environmental conditions and exposures to develop indices for use in environmental health studies.[14] The air domain EQI was constructed using data on criteria and hazardous air pollutants; the water domain EQI was constructed using data on overall water quality, water contamination, recreational water quality, domestic water use, atmospheric deposition, drought, and chemical contamination; the land domain EQI was constructed using data on the agricultural environment, pesticides, facilities, soil contamination and potential for radon pollution; the built environment domain was constructed using data on traffic, transit access and participation, pedestrian safety, business and retail environments, and public housing; finally, the sociodemographic domain EQI was constructed using socioeconomic and crime data.[14] Like the composite EQI, domain-specific EQI values were scaled so that higher values indicated worse environmental and sociodemographic conditions.

To understand county-level diabetes prevalence trajectories from 2004 to 2017, we employed latent growth mixture models to counties in each of the four RUCC strata using the lcmm package in R.[15] This method allowed us to identify unobserved subgroups of counties within RUCC strata that shared similar trajectories of age-adjusted diabetes prevalence between 2004 and 2017.[16] We used a random quadratic variance structure for its flexibility, which allowed counties' diabetes prevalence trajectories to vary within classes by their initial (i.e., year 2004) prevalence estimates, the overall magnitude of change in diabetes prevalence between 2004 and 2017, and rate of change in diabetes prevalence estimates by year. We chose the optimal number of classes for final model selection using the Bayesian Information Criteria (BIC), with the lowest value indicating the most parsimonious model. For RUCC strata 1, 3, and 4, we examined models with 1–4 latent classes. However, for RUCC 2, we evaluated models for 1–6 latent classes, as a model with 4 latent classes appeared to be optimal, and we wanted to be certain that increasing numbers of latent classes did not result in a better fit.

After identifying the optimal number of latent classes for each of the four RUCC strata, we calculated the mean and standard deviations of the overall EQI and each of the five domain-specific EQIs for all counties by RUCC strata and latent class. We then compared these mean EQI values by latent class of county-level diabetes prevalence trajectories and within RUCC strata using *t* tests or analysis of variance (ANOVA), where appropriate for the number of optimal classes identified (i.e., 2 classes vs. 3 or more classes). To better understand distributions of EQI values, we generated stratified histograms of EQI values by latent class and RUCC strata.

Results

A total of 3,137 counties in the United States that had both EQI data and assigned RUCC categories were included in this analysis, representing 99.8% of all US counties, with 1,089 counties in RUCC 1; 323 counties in RUCC 2; 1,057 counties in RUCC 3; and 668 counties in RUCC 4 (Table 1). The number

Table 1.

Summary of latent growth mixture model results by RUCC strata.

RUCC strata	Counties (n) per RUCC strata	Number of latent classes	BIC
Metropolitan urbanized (RUCC 1)	1,089	1	49,631.07
		2	48,066.25[a]
		3	49,038.51
		4	48,577.03
Nonmetro urbanized (RUCC 2)	323	1	14,640.98
		2	14,116.48
		3	14,440.54
		4	14,106.35[a]
		5	14,141.29
		6	14,295.69
Less urbanized (RUCC 3)	1,057	1	54,896.38
		2	53,044.82
		3	52,745.03[a]
		4	53,098.35
Thinly populated (RUCC 4)	668	1	35,090.98
		2	36,121.06
		3	33,833.64[a]
		4	34,129.57
Total counties (n)	3,137		

[a]Optimal class.

BIC indicates Bayesian Information Criterion.

of optimal latent classes, as determined by BIC, differed across RUCC strata (Table 1). Within each of these strata, there was substantial variation in individual county trajectories in diabetes prevalence over time, especially in the later years of the study period, which we displayed for a randomly selected 50 counties per RUCC strata (Figure 1).

We display the diabetes prevalence trajectories for 2004–2017 for all 3,137 counties in this analysis by RUCC strata and within RUCC strata class assignment (Figure 2). Overall, there was increased variation in diabetes prevalence in the later versus earlier years of this analysis, and the assigned classes appeared to identify counties with similar prevalence trajectories over this time period, as was intended. Within RUCC strata, class differences were more visually apparent with fewer numbers of classes (i.e., RUCC 1 with 2 classes vs. RUCC 2 with 4 classes), although classes were distinguishable in all four RUCC strata with 2,3, or 4 optimal classes.

Mean values of the overall EQI and domain-specific EQI all significantly differed ($P < 0.05$) by class within RUCC strata, with the exception of the built EQI among thinly populated (RUCC 4) counties ($P = 0.06$, Table 2). For metropolitan urban counties (RUCC 1), higher mean EQI values were observed in class 1, the class of counties that did not experience steep increases in diabetes prevalence between 2004 and 2017. The pattern was similar in RUCC 1 counties for most of the domain-specific EQI values (air, water, land, and built environments) but not for the

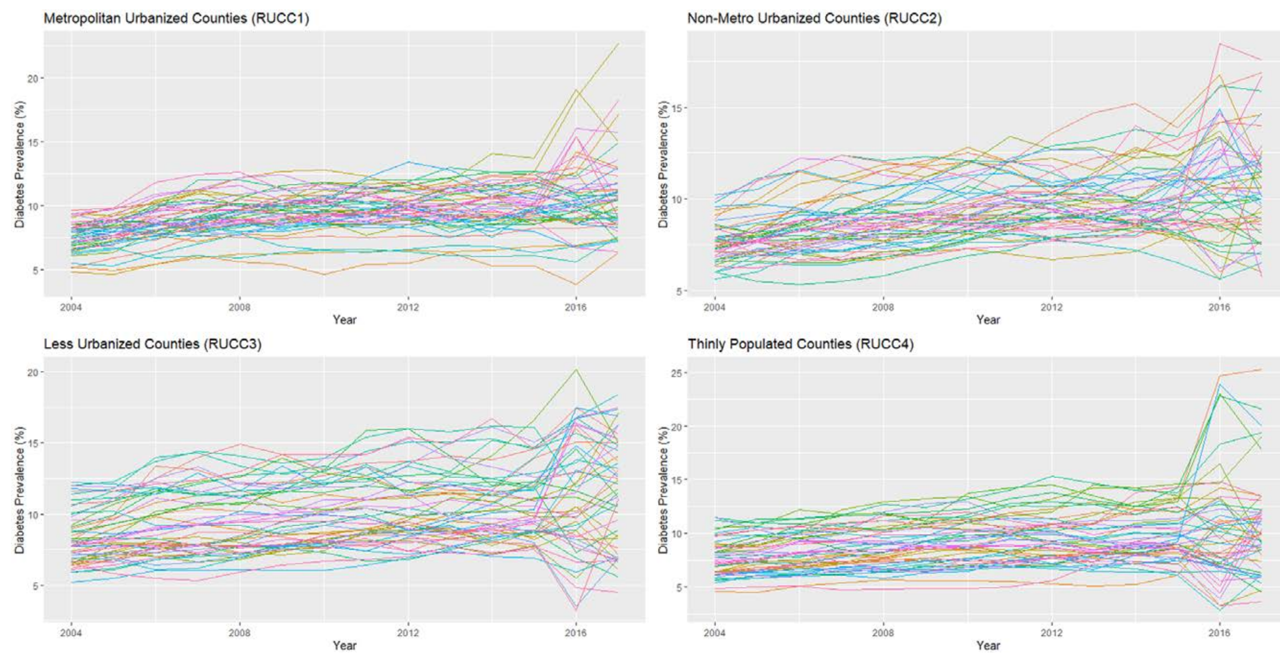

Figure 1. Random sample of 50 counties diabetes prevalence trajectories by each RUCC strata, 2004–2017.

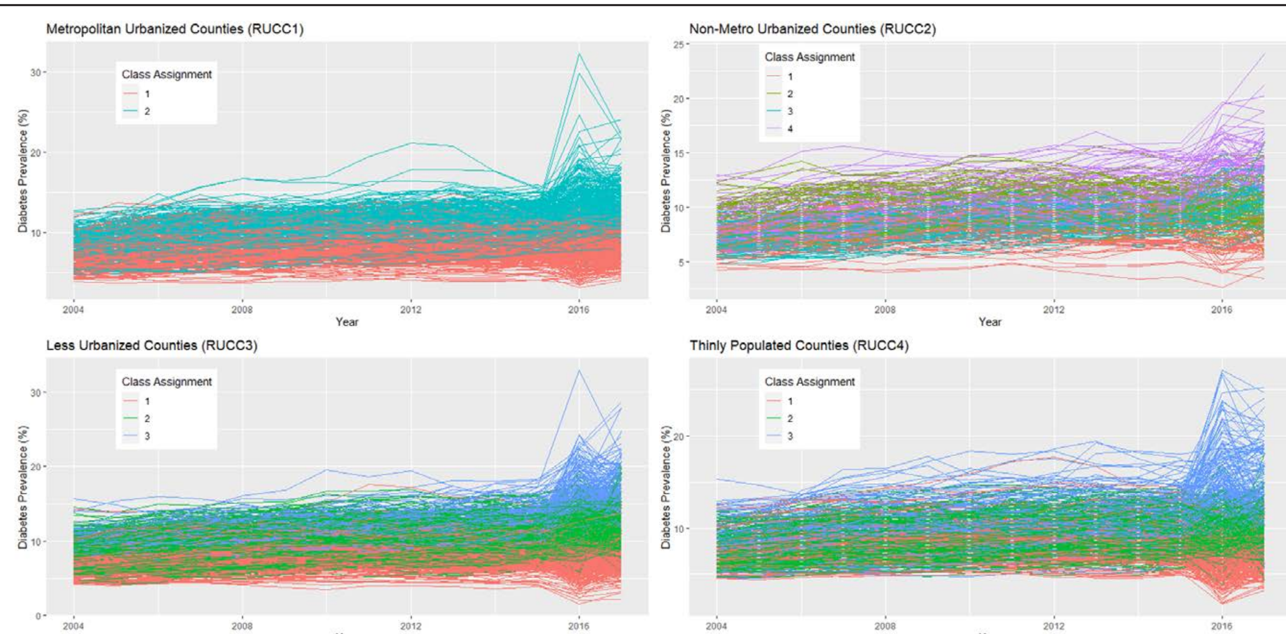

Figure 2. Diabetes prevalence trajectories by RUCC category and optimal number of latent classes, 2004–2017.

Table 2.

Summary of RUCC categories, counties per optimal latent growth class, and mean EQI values, including domain-specific EQI results.

RUCC category	Counties (n)	Class	EQI, mean (SD)	*P* value[a]	Air EQI, mean (SD)	*P* value[a]	Water EQI, mean (SD)	*P* value[a]	Land EQI, mean (SD)	*P* value[a]	Built EQI, mean (SD)	*P* value[a]	Sociodemographic EQI, mean (SD)	*P* value[a]
Metropolitan urbanized (RUCC 1)	586	1	0.26 (0.99)		0.09 (1.04)		0.07 (1.01)		0.12 (0.98)		0.23 (0.99)		−0.22 (1.03)	
	503	2	−0.31 (0.93)	<0.001	−0.10 (0.94)	0.002	−0.08 (0.98)	0.01	−0.13 (1.01)	<0.001	−0.27 (0.94)	<0.001	0.26 (0.90)	<0.001
Nonmetro urbanized (RUCC 2)	61	1	0.39 (1.06)		−0.53 (1.19)		0.36 (0.86)		0.03 (1.29)		0.58 (1.13)		0.60 (0.96)	
	80	2	−0.15 (0.88)		0.23 (0.83)		−0.19 (1.03)		−0.21 (0.98)		−0.03 (0.82)		−0.13 (0.78)	
	88	3	0.23 (0.89)		−0.14 (0.98)		0.16 (0.93)		0.36 (0.56)		0.03 (0.90)		0.12 (1.03)	
	94	4	−0.34 (1.03)	<0.001	0.28 (0.86)	<0.001	−0.22 (1.04)	<0.001	−0.18 (1.04)	<0.001	−0.38 (0.98)	<0.001	−0.39 (0.97)	<0.001
Less urbanized (RUCC 3)	386	1	0.33 (0.97)		−0.18 (1.08)		0.18 (0.94)		0.19 (1.07)		0.30 (1.07)		0.35 (1.01)	
	445	2	0.00 (0.95)		0.05 (0.98)		−0.05 (1.03)		0.01 (0.90)		−0.04 (0.89)		0.01 (0.91)	
	226	3	−0.53 (0.85)	<0.001	0.24 (0.80)	<0.001	−0.20 (1.00)	<0.001	−0.32 (0.93)	<0.001	−0.38 (0.75)	<0.001	−0.61 (0.84)	<0.001
Thinly populated (RUCC 4)	216	1	0.07 (1.12)		−0.35 (1.00)		0.08 (0.93)		0.05 (1.07)		−0.02 (1.22)		0.19 (0.99)	
	260	2	0.17 (0.91)		0.01 (0.94)		−0.04 (1.03)		0.10 (0.93)		0.10 (0.91)		0.15 (0.88)	
	192	3	−0.28 (0.89)	<0.001	0.40 (0.92)	<0.001	−0.03 (1.02)	<0.001	−0.14 (0.86)	0.03	−0.12 (0.82)	0.06	−0.43 (1.04)	<0.001

[a]*P* values obtained from ANOVA (RUCC2, RUCC3, RUCC 4) and two-sampled *t* tests (RUCC1).

sociodemographic EQI, where higher values (indicating worse socioeconomic conditions) were present for counties in class 2, which had greater increases in diabetes prevalence over time. Among non-metro urbanized counties (RUCC 2), there were no clear patterns in differences between mean EQI values, or the mean domain-specific EQI values for air, water, land, built, or sociodemographic environments by class.

Among less urbanized (RUCC 3) and thinly populated (RUCC 4) counties, mean EQI values for the overall EQI and water, land, built, and sociodemographic EQIs were highest, indicating worse environmental conditions, among class 1 for these RUCC strata, which did not experience increases in diabetes prevalence between 2004 and 2017. These values decreased linearly with increasing class (i.e., classes with increasing diabetes prevalence), the opposite direction of what we hypothesized. However, among less urbanized and thinly populated counties, mean values for the air EQI increased with increasing class, suggesting that worse air quality environments were correlated with classes of counties that experienced increases in diabetes prevalence over this time. To better understand this finding, we generated histograms of county-level air domain EQI values by RUCC strata and class (Figure 3) and confirmed that air EQI values differed by class among less urbanized (RUCC 3) and thinly populated (RUCC 4) counties, with greater air EQI values among class 3, which experienced the steepest increases in diabetes prevalence between 2004 and 2017.

Discussion

Although there was substantial variation in diabetes prevalence trajectories between 2004 and 2017 among 3,137 counties in the United States, we identified latent classes of counties with similar trajectories in diabetes prevalence among four RUCC strata: metropolitan urbanized, non-metro urbanized, less urbanized, and thinly populated counties. Within RUCC strata, we identified the optimal number of latent classes, ranging from 2 to 4. Class number assignment corresponded to the relative increase in diabetes prevalence over this time, where counties in class 1 among each RUCC strata generally did not experience steep increases in diabetes prevalence, and counties in classes numbered higher (i.e., 2–4) generally experienced steeper increases in diabetes prevalence over this time. These findings confirm that not all counties in the United States experienced increases in diabetes prevalence between 2004 and 2017, and among those that did, some counties increased by more than others. Thus, researchers can identify counties with similar experiences in changes in diabetes prevalence for targeted intervention and prevention strategies.

Our study found that county-level mean values of the EQI, including the domain-specific EQI values, differed by class of diabetes prevalence trajectories among counties in each of the four RUCC strata. In contrast to our original hypothesis, we observed higher mean EQI values, indicating worse environmental quality, among counties in class 1 of each RUCC strata, comprised of counties which did not experience steep increases in diabetes prevalence. This finding can be due to the limitations of the univariate analysis; perhaps any mechanism underlying associations between poor environmental quality and diabetes prevalence is also influenced by sociodemographic conditions, health care access, and the underlying health conditions of the county's population. Although we evaluated associations between the sociodemographic EQI in our analysis, we did not account for these other conditions at the county level.

However, in support of our original hypothesis, we observed differences in findings by urban and rural county classifications. Among the metropolitan counties (RUCC 1), the sociodemographic EQI was higher (indicating worse sociodemographic conditions) among the counties experiencing increases in diabetes prevalence, although the domain-specific EQI measures show the opposite. It is unclear why the trend does not hold

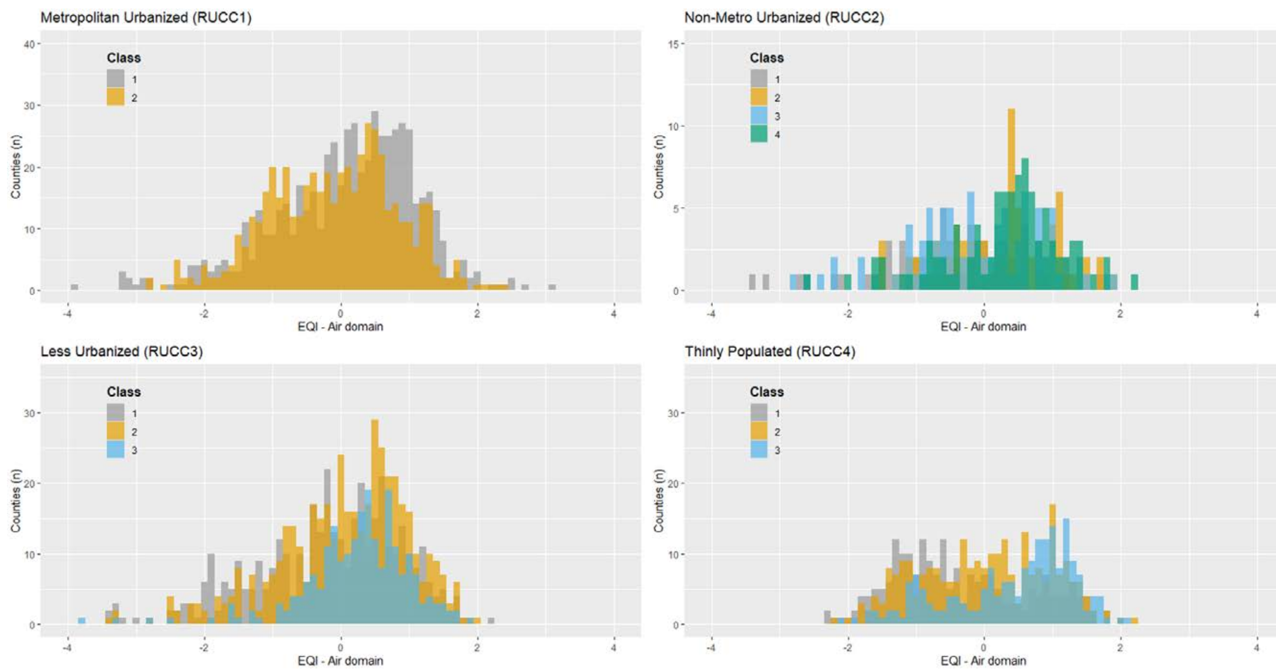

Figure 3. Histograms of air domain-specific EQI values, stratified by RUCC category and latent class.

across domains of the EQI but is likely related to the characteristics of the counties that distinguish the latent classes. Future work should explore specific characteristics of the counties and their impact on the associations with the EQI domains.

Associations between county class and EQI values among non-metro urbanized counties (RUCC 2) were not clear for any of the EQI domains. Among more rural RUCC strata, less urbanized (RUCC 3) and thinly populated (RUCC 4) counties demonstrated higher EQI values with increasing class for only the air EQI, suggesting that more rural counties with worse air quality experienced increases in diabetes prevalence. While there are some limitations to ecologic analyses, application of the latent growth mixture model approach allowed us to identify counties within RUCC class that had similar diabetes prevalence trajectories, and we were able to identify some associations between sociodemographic and air quality conditions with these trajectories, which differed by urban/rural RUCC classifications. These urban/rural differences may be attributable to different individually factors differentially influencing diabetes trends over time across varying levels of urbanicity, a subject of future research.

Understanding associations between mean EQI values and county-level diabetes prevalence trajectories, as well as the urban/rural differences in these associations, requires examination of data sources used to construct the EQI. Data used to construct the sociodemographic EQI consisted of US Census Bureau data on county-level population density, race, socioeconomic characteristics, housing and land use as well as county-level violent crime and property crime counts and rates from the Federal Bureau of Investigation Uniform Crime Reports.[14] Contextual sociodemographic characteristics can impact an individual's diabetes risk[7]; however, the same may not be true at the county-level for rural counties, reflecting a differing spatial extent. Conversely, the EQI air domain consists of data reflective of criteria air pollutants (CAPs): particulate matter, carbon monoxide, ozone, lead, nitrogen dioxide, and sulfur dioxide; and hazardous air pollutants (HAPs), which include over 175 various toxic substances released into the air from industrial processes.[14] Each of these air pollutants have differing spatial distributions with substantial spatial heterogeneity,[17–19] although particulate matter less than 2.5 μm in diameter ($PM_{2.5}$) has less variability across large distances due to its small aerodynamic particle size.[20] This air pollutant has been increasingly implicated in the development of T2D,[21,22] and it is possible that the association between the air EQI and increases in diabetes prevalence trajectories observed among rural counties is reflective of the spatial distribution of $PM_{2.5}$. Of course, longitudinal studies with individual-level exposure and outcome data would help better understand this finding.

Our findings are consistent with a growing literature suggesting differential diabetes risk among urban and rural communities. For example, in Jagai et al's[10] analysis of the EQI and county-level diabetes prevalence, poor environmental quality was associated with lower diabetes prevalence estimates among RUCC 3 and RUCC 4 counties after controlling for obesity prevalence and leisure time physical inactivity prevalence. We found that counties in RUCC 3 and RUCC 4 that had steeper increases in diabetes prevalence over time had higher mean air EQI, suggesting poor air quality among these counties. It is unclear exactly why these urban–rural differences in associations with environmental factors and diabetes outcomes exist, but these could be due to differences in how individuals interact with their environments in urban versus rural environments,[23,24] differential access to care,[25] and objective differences in clinical factors related to diabetes control.[26,27] Further, differential item functioning could contribute to observed urban-rural differences in our results.

In contrast to our findings, Jagai et al[10] found that poor sociodemographic environments were associated with increased diabetes prevalence in all four RUCC strata after controlling for obesity prevalence and leisure time physical inactivity prevalence. It is possible that our findings differed from these findings due to the differing nature of our analysis; our analysis focused on identifying counties with similar trends in diabetes prevalence over time, and associations with EQI variables were descriptive and not adjusted for county-level obesity prevalence and leisure time physical inactivity prevalence, whereas Jagai et al's[10] analysis focused on understanding county-level prevalence as a function of the EQI and adjusted for these county-level covariates. Thus, our reported associations of mean EQI values and diabetes class trajectory should be interpreted with caution, as the associations reported are descriptive and warrant further investigation, with a different study design, to understand causality.

Our study had some limitations. First, the US EPA EQI included data from 2006 to 2010 and thus did not include data before 2004, the first year of diabetes prevalence estimates included in this analysis. Second, diabetes prevalence estimates were calculated annually and considered the raw number of adults in each county as the denominator, not accounting for any county-level demographic shifts over time, which could complicate findings. These estimates also included all types of diabetes and did not specifically identify T2D prevalence. Finally, the latent growth mixture models employed in this analysis did not account for other factors that may influence the association between diabetes trends over time and EQI. In this sense, our latent classes of diabetes prevalence trajectories were agnostic to county-level covariates that also impact diabetes risk and were purely descriptive of diabetes prevalence trends over time.

There were several strengths of this analysis. First, we leveraged 14 years of national diabetes prevalence data from the CDC, estimated from the National Health Interview Survey.[12] Second, our application of latent growth mixture modeling to understand diabetes prevalence trajectories in the United States is novel and helps to understand counties that experienced differential changes in diabetes prevalence over this 14-year period from 2004 to 2017. This is especially important for prioritizing and targeting interventions to specific counties to manage diabetes risk. Finally, we leveraged objective environmental data from the US EPA EQI to understand multiple dimensions of environmental risk factors for adverse health outcomes.

We identified latent classes of counties with similar trends in diabetes prevalence between 2004 and 2017 among four RUCC strata of 3,137 counties in the United States. Among these, we observed different associations with domain-specific EQI, particularly sociodemographic and air EQIs, by rural/urban counties. These findings suggest that associations between environmental factors and diabetes prevalence trends differ by rurality. Future studies with individual, longitudinal data, and systematic accounting of individual and community-level risk factors and rurality should examine specific air pollutants and sociodemographic factors that could be etiologically responsible for increases in diabetes prevalence.

References

1. Centers for Disease Control and Prevention. National Diabetes Statistics Report. Atlanta, GA: Centers for Disease Control and Prevention, U.S. Dept of Health and Human Services, 2020.
2. Menke A, Casagrande S, Geiss L, Cowie CC. Prevalence of and trends in diabetes among adults in the United States, 1988-2012. *JAMA*. 2015;314:1021–1029.
3. Harding JL, Pavkov ME, Magliano DJ, Shaw JE, Gregg EW. Global trends in diabetes complications: a review of current evidence. *Diabetologia*. 2019;62:3–16.
4. Thibault V, Bélanger M, LeBlanc E, et al. Factors that could explain the increasing prevalence of type 2 diabetes among adults in a Canadian province: a critical review and analysis. *Diabetol Metab Syndr.* 2016;8:71.
5. Bellou V, Belbasis L, Tzoulaki I, Evangelou E. Risk factors for type 2 diabetes mellitus: An exposure-wide umbrella review of meta-analyses. *PLoS One*. 2018;13:e0194127.
6. Dendup T, Feng X, Clingan S, Astell-Burt T. Environmental risk factors for developing type 2 diabetes mellitus: a systematic review. *Int J Environ Res Public Health*. 2018;15:E78.
7. Bilal U, Auchincloss AH, Diez-Roux AV. Neighborhood environments and diabetes risk and control. *Curr Diab Rep*. 2018;18:62.
8. Messer LC, Jagai JS, Rappazzo KM, Lobdell DT. Construction of an environmental quality index for public health research. *Environ Health*. 2014;13:39.
9. Lobdell D, Jagai J, Messer L, et al. *Environmental Quality Index - Overview Report (2000-2005) (Final, 2014)*. Washington, DC: U.S. Environmental Protection Agency, 2014.
10. Jagai JS, Krajewski AK, Shaikh S, Lobdell DT, Sargis RM. Association between environmental quality and diabetes in the USA. *J Diabetes Investig*. 2020;11:315–324.
11. CDC. US Diabetes Surveillance System website. Available at: https://www.cdc.gov/diabetes/data Accessed March 30, 2021.
12. National Center for Health Statistics C. *Survey Description, National Health Interview Survey.* Centers for Disease Control and Prevention, 2017.
13. USDA. Rural-Urban Continuum Codes. In: *Economic Research Service DoA*, ed, 2021.
14. EPA. US. Creating an Overall Environmental Quality Index - Technical Report (2000-2005) (Final, 2014). In: *Agency USEP*, ed. Washington, DC, 2014.
15. Lennon H, Kelly S, Sperrin M, et al. Framework to construct and interpret latent class trajectory modelling. *BMJ Open*. 2018;8:e020683.
16. Ram N, Grimm KJ. Growth Mixture Modeling: A Method for Identifying Differences in Longitudinal Change Among Unobserved Groups. *Int J Behav Dev.* 2009;33:565–576.
17. McCarthy Michael C, O'Brien Theresa E, Charrier Jessica G, Hafner Hilary R. Characterization of the Chronic Risk and Hazard of Hazardous Air Pollutants in the United States Using Ambient Monitoring Data. *Environ Health Perspect*. 2009;117:790–796.
18. Scheffe RD, Strum M, Phillips SB, et al. Hybrid modeling approach to estimate exposures of Hazardous Air Pollutants (HAPs) for the National Air Toxics Assessment (NATA). *Environ Sci Technol.* 2016;50:12356–12364.
19. Bell ML, Dominici F, Ebisu K, Zeger SL, Samet JM. Spatial and temporal variation in PM(2.5) chemical composition in the United States for health effects studies. *Environ Health Perspect.* 2007;115:989–995.
20. Pinto JP, Lefohn AS, Shadwick DS. Spatial variability of PM2.5 in urban areas in the United States. *J Air Waste Manag Assoc.* 2004;54:440–449.
21. Pearson JF, Bachireddy C, Shyamprasad S, Goldfine AB, Brownstein JS. Association between fine particulate matter and diabetes prevalence in the U.S. *Diabetes Care.* 2010;33:2196–2201.
22. Lao XQ, Guo C, Chang LY, et al. Long-term exposure to ambient fine particulate matter (PM2.5) and incident type 2 diabetes: a longitudinal cohort study. *Diabetologia.* 2019;62:759–769.
23. Joens-Matre RR, Welk GJ, Calabro MA, et al. Rural–Urban Differences in Physical Activity, Physical Fitness, and Overweight Prevalence of Children. *J Rural Health*. 2008;24:49–54.
24. Cohen SA, Greaney ML, Sabik NJ. Assessment of dietary patterns, physical activity and obesity from a national survey: rural-urban health disparities in older adults. *PLoS One.* 2018;13:e0208268.
25. Krishna S, Gillespie KN, McBride TM. Diabetes burden and access to preventive care in the rural United States. *J Rural Health*. 2010;26:3–11.
26. Mercado CI, McKeever Bullard K, Gregg EW, Ali MK, Saydah SH, Imperatore G. Differences in U.S. Rural-Urban Trends in Diabetes ABCS, 1999-2018. *Diabetes Care.* 2021;44:1766–1773.
27. Dugani SB, Mielke MM, Vella A. Burden and management of type 2 diabetes in rural United States. *Diabetes Metab Res Rev.* 2021;37:e3410.