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**Tracking Changes in Walkability Over Time:
How Our Neighborhoods Are Developing and
What it Means for Health Surveillance**

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Tracking Changes in Walkability Over Time: How Our Neighborhoods Are Developing and What it Means for Health Surveillance

Abstract – An increasing body of evidence highlights the health-supportive role walkable environments can play by increasing active and reducing sedentary travel, thus lowering chronic disease risks. With increasing urbanization, it is important to assess how built environment characteristics are changing over time. In this context, understanding the extent of geographic and social disparities in the distribution of changes in walkability is also warranted. This study presents a nationwide assessment of how physical environment characteristics known to impact health and welfare are changing over time in the U.S. We integrate longitudinal data for over 164,000 participants in the American Cancer Society’s prospective Cancer Prevention Study (CPS-3) cohort with objectively assessed built environment data at two time points (2013 and 2020). Descriptive and longitudinal change detection modeling of a geographically and ethnically diverse national sample of over 109,000 non-movers revealed some improvements in urban compactness, street connectivity, transit accessibility, urban diversity, and overall walkability levels. Changes in walkability across U.S. regions and the urban-rural continuum exhibited geographic disparities. Participants in rural areas and small towns experienced a modest reduction in walkability, whereas the reverse was observed for those in urban areas. Walkability increased over time for all age and racial groups but exhibited considerable variations. The increase in walkability over time was greatest for Hispanics and Blacks compared to non-Hispanic Whites. Results provide background trends and can inform walkability interventions to reduce geographical inequities for the most underserved. Implications of our work for future research are discussed.

Keywords: Walkability, sustainability, geographic disparities, spatial justice, health.

1. INTRODUCTION & BACKGROUND

Active transportation and physical activity have significant mental and physical health benefits. Greater physical activity and active transportation are associated with improved mental health (Paluska and Schwenk 2000, Landers and Arent 2007, Dadvand et al. 2016, White et al. 2017, Marconcin et al. 2022) and lowered mortality and morbidity from chronic diseases (Friedenreich and Orenstein 2002, Patel et al. 2005, Furie and Desai 2012, Schauder and Foley 2015, Dixon-Suen et al. 2022). Relationships between transportation sedentary time and screen-based or leisure-time sitting with obesity are also well documented (Frank et al. 2004, McCormack and Virk 2014, Patel et al. 2018). Active travel and physical activity are also correlated with lower mortality and morbidity from infectious diseases (such as COVID-19) (Cho et al. 2021, Salgado-Aranda et al. 2021, Sallis et al. 2021, Wali 2023). Yet, in 2019, over 17% of American adults were not physically active. Physical inactivity rates varied from 17.3% to 47.7% among different states in the U.S. (CDC 2020). Identifying mechanisms to increase physical activity levels thus remains a pressing research need and key public health priority (Boutari and Mantzoros 2022, Santos et al. 2023).

A broad spectrum of cross-sectional studies documents the relationships of built and natural environment with individuals’ travel patterns (Frank et al. 2006, Saelens and Handy 2008, Cao 2010, Kang et al. 2017, Hou et al. 2021, Wang et al. 2021), physical and mental health (Müller-Riemenschneider et al. 2013, Gascon et al. 2015, Chen et al. 2022, Howell and Booth 2022, Hou et al. 2024, Liu and Liao 2024), and associated health care costs. Longitudinal evidence on built environment and transportation infrastructure impacts is now also growing (MacDonald et al. 2010, Brown et al. 2015, Creatore et al. 2016, Zhou et al. 2017, Kärmeniemi et al. 2018, Tcymbal et al. 2020, Feyissa et al. 2024). Although environmental characteristics are strongly linked with sustainable travel and population health (Sallis and Glanz 2006), it remains a challenge to create and retrofit built environments to promote sustainability and health (Wali et al. 2021).

Given the significant influence of the built environment on activity patterns, it becomes important to assess how our neighborhoods as socio-physical systems (SPS) are changing over time (Carney et al. 2017,

Richardson et al. 2019). Doing so is a new form of health surveillance that enables an understanding of how neighborhood features (e.g., walkability, land use, and transit accessibility) are structurally changing in relation to each other and with respect to social vulnerability. Doing so further supports targeting investments within communities most in need. In this context, a better comprehension of the changing nature of neighborhood-level spatial justice inequalities over time is also warranted. We use the term “spatial justice” in the context of equitable distribution of resources, opportunities, and services across different geographic areas within society (Soja 2013). Finally, tracking environmental changes over time enables an assessment of how well cities and communities adapt to major challenges, including chronic disease control, climate change, and social inequality. We apply an interconnected 4-tiered neighborhood surveillance structure, e.g., as in (Frank and Wali 2024). Physical environment changes over time (Tier 1) form the foundation impacting travel and activity choices (Tier 2), which in turn influence environmental quality (Tier 3) and overall welfare (Tier 4). Consistent national-level fine-resolution physical environment data collected at multiple time points did not exist until recently. This precluded the ability to assess how physical environments are changing throughout the United States relative to demographics and spatial factors. To our knowledge, only one study so far has empirically assessed physical environment changes over time across the United States (Frank and Wali 2024). The study documented an increase in walkability over time across the nation, but with significant heterogeneity across urban and rural areas ¹. Nonetheless, the study was ecological (census tract-level) in nature and did not evaluate changes in walkability over time at the individual level.

The present study contributes to the literature by leveraging individual-level longitudinal data to conduct a nationwide assessment of how physical environment characteristics have evolved in the U.S. We integrate longitudinal data for over 164,000 participants in the American Cancer Society’s prospective Cancer Prevention Study-3 (CPS-3) cohort with objectively assessed built environment data at two points (2013 and 2020). We present longitudinal descriptive and inferential analyses to assess how neighborhood physical characteristics have evolved for a national sample of over 109,000 non-movers (i.e., individuals who did not relocate during the study period). We assess social and geographic equity in the distribution of walkability across US regions, neighborhood type (level of urbanicity), and demographic/socioeconomic indicators descriptively and through longitudinal change detection models. For readability and conciseness, we use the term ‘longitudinal change detection models’ to refer to a longitudinal regression model used to model (detect) changes in walkability over time. While this study focuses on non-movers, we briefly discuss a pooled analysis of how physical environments changed over time for both movers and non-movers.

The paper is structured as follows. Section 2 provides an overview of the methodology, including integration of the CPS-3 cohort and environmental data at two time points, empirical context, and longitudinal analysis methods. Section 3 presents results from the descriptive analysis and longitudinal change detection modeling of how changes in neighborhood physical characteristics vary across space and demography. In section 4, we synthesize the results in light of the literature and discuss the limitations and implications of our findings. We conclude the study in Section 5.

¹ We note that several studies have evaluated changes in walkability characteristics over time in specific areas (Creatore et al. 2016, Timmermans et al. 2021) or in the context of specific interventions, e.g., transit interventions (Stokes et al. 2008, Wali et al. 2022, Kato et al. 2024) and greenway projects (Stappers et al. 2023). For example, Timmermans et al. (2021) evaluated changes in walkability in relation to changes in walking activity for a sample of 668 non-movers in Amsterdam. Within-person changes in environmental measures were documented, including both gains and declines in walkability metrics over time (Timmermans et al. 2021). Similarly, an ecological study of Southern Ontario neighborhoods in Canada reported fairly stable neighborhood walkability scores over time (Creatore et al. 2016). These studies made important contributions but are not directly relevant to the present study given their focus on assessing changes in walkability in relation to changes in walking and/or health outcomes. Additionally, such studies are limited to specific cities or small survey cohorts. As noted above, the ability to evaluate changes in walkability itself and how such changes may relate to the social fabric of our communities is fundamental to a performance-based system that spatially links environmental resources to communities that most need them.

2. METHODOLOGY

2.1. Data Sources and Spatial Integration

The study integrates two key data sources: (1) individual-level demographic and health data from the American Cancer Society's Cancer Prevention Study – 3 (CPS-3) cohort (Patel et al. 2017), and (2) census-block group (CBG) level environmental data from the Smart Location Database and National Environmental Database (NED). The integration of the CPS-3 cohorts and NED data was performed across two time points – 2013 and 2020. The environmental data from both time points were spatially joined to the Census block group containing the home locations of CPS-3 participants. Census block group Federal Information Processing System (FIPS) codes extracted from the home addresses of participants were used to link CPS-3 cohorts with environmental data.

2.1.1. Overview of CPS-3 Survey Data

The CPS-3 cohort data included in this study contain individual-level demographic and health data obtained from two survey waves from the Baseline (2013) and Follow-up (2020) periods. Baseline and follow-up periods are referred to as Time 1 and Time 2. Detailed individual-level data are available on income, education, age, marital status, race, and sex. We used relevant variable coding to recode demographic variables to the same levels across the two survey waves before integration². Using the state FIPS codes for each participant, we coded the residential location of each participant's home location into one of nine U.S. census divisions (Census 2020). These divisions are New England, Middle Atlantic, South Atlantic, East South Central, East North Central, West South Central, West North Central, Mountain, and Pacific. Information on neighborhood type (metropolitan, micropolitan, and small town/rural) was also incorporated. We define “neighborhood type” as whether a census block group is located in metropolitan, micropolitan, or small town/rural area. Besides demographic variables, the CPS-3 cohort includes detailed information on key behavioral and health outcomes. These outcomes, while not the focus of the present study, include moderate-to-vigorous intensity physical activity (MVPA), walking hours, body mass index, chronic disease, and cancer outcomes (Patel et al. 2017, Rees-Punia et al. 2021). The empirical context involves an integrated analysis of time-varying residential environment features over time in relation to individuals' characteristics in the CPS-3 cohort. Figure 1 shows the initial and final study sample sizes. The Time 1 and Time 2 surveys included 252,404 and 164,555 participants, respectively. A total of 148,147 participants had both Time 1 and Time 2 survey data with complete information on residential addresses and environmental data (described in the next section). Of these, around 73% of the participants did not relocate in the study period. Non-movers in this study are defined as those who did not relocate to a different census block group. We were only able to identify inter-census block group movers since we did not have access to the street-level residential addresses of the participants. The final longitudinal database is comprised of two rows of survey data for each non-mover in the database (for each Time 1 and Time 2), with corresponding neighborhood-level (census block group-level) environmental data described next³.

² For example, the baseline survey coded marital status as: (1) married/living as married, (2) separated/divorced, (3) widowed, (4) never married, (9) unknown, whereas the follow-up survey coded marital status variable as: (1) married, (2) partner, (3) never married, (4) divorced, (5) separated, (6) widowed, (9) unknown. Thus, we created dummy variables representing marital status in baseline and follow-up periods for the following categories: married/living with a partner, separated/divorced, widowed, never married, and unknown. A similar procedure was followed for age and income variables.

³ Census block groups are among the most granular spatial units used by the U.S. Census Bureau for which most demographic factors are publicly reported (Census 2018). They have population and housing thresholds of 600 – 3,000 residents and 240 – 1,200 housing units, respectively (Census 2018). Most contain 1,000 to 1,500 residents. Given our sample of 109,146 participants across nine regions, the block groups in our study are considerably heterogeneous in terms of the built environment as reflected in our results discussed later. However, per the IRB-approved study protocol, the final analysis file available to us includes demographic covariates and walkability data at two time points but excludes any granular geographic identifiers, such as census block group FIPS codes. The key purpose is to ensure anonymity of study respondents and make it impossible to locate or identify respondents. Consequently, we are unable to provide exact population statistics (e.g., mean, min, max acreage/population) for participants' specific block groups.

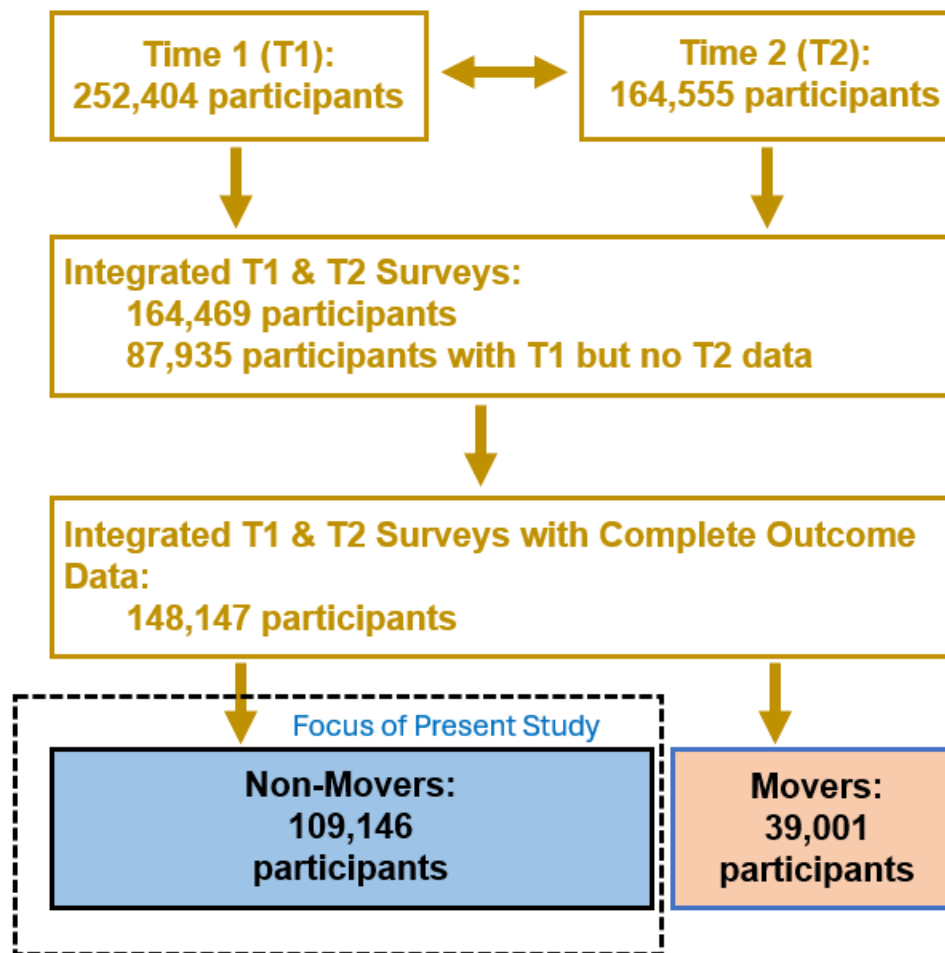


FIGURE 1. Study Sample Sizes.

2.1.2. Overview of Environmental Data

The environmental measures of interest include multiple built environment measures related to urban density (compactness), diversity, design (street connectivity), distance to transit, and a composite walkability index ⁴. *Density* captures urban compactness and proximity represented by “gross” housing units per acre. This walkability metric is long known to be correlated with active travel and health outcomes (Steiner 1994, Cervero and Kockelman 1997, Lawrence 2002, Ewing and Cervero 2010). *Employment entropy* is measured through a 5-tier and 8-tier set of employment mix variables representing the evenness of different job types within a census block group. This measure of heterogeneity of activities also captures proximity and uses employment mix to proxy for diversity of actual land uses and floor space across different activities. These land use diversity measures are shown to predict travel patterns (Frank and Pivo 1994, Krizek 2003, Ewing and Cervero 2010). *Street connectivity* is the number of pedestrian-accessible intersections per sq. mile and captures route directness. This street connectivity measure is widely used in the transportation planning and public health literature examining the built environment relationships with travel patterns, physical activity, and health (Cho et al. 2009, Ewing and Cervero 2010). *Transit accessibility* is essential for many people to access important goods and services such as food, health care services, employment, and green space (Sengupta et al. 2013). Barriers to transit can negatively affect health outcomes. Transit access can also increase physical activity and reduce air pollution and healthcare costs (Sener et al. 2016). Neighborhood-level access to transit was captured using two key measures: distance to

⁴ A listing of all built environment measures evaluated for this analysis is included in Table A1 of Appendix A.

the nearest transit stop and counts of transit stops. Please see Appendix A for details on individual environmental measures. An important measure of travel behavior related to automobile usage is annual household vehicle miles traveled (VMT). Data on household VMT was incorporated as a proxy for auto-oriented travel behavior in a neighborhood. Finally, a composite walkability index was used that measures overall walking-supportive environmental features. The walkability index is calculated on a 1-20 scale, with 20 indicating the highest level of walkability across four differentially weighted component measures (Thomas and Reyes 2024). We note that the U.S. EPA walkability index does not incorporate all built environment measures outlined above and is based on a subset of four individual environmental measures: household and employment entropy, employment mix, street connectivity, and distance to the nearest transit stop⁵. The walkability index has been validated in past studies to predict walking/travel demand (e.g., see Watson et al. (2020), Bucko et al. (2021), Pae and Akar (2025), and Li and Rodriguez (2024)) and disease outcomes (see, for example, Makhoul et al. (2023) and Wali (2023)). The built environment and walkability measures are obtained from the National Environmental Database and U.S. EPA Smart Location Database, developed by the U.S. Environmental Protection Agency for Time 1 and updated by Urban Design 4 Health for Time 2 (Chapman et al. 2021).

To achieve the most accurate comparison between multiple time points, the same data sources, methods, and data processing techniques should be used. For the comparisons presented here, both time points used the same 2010 Census block group boundaries to ensure consistent metric calculation and summarization. Additionally, when calculating environmental measures, supplemental base data was kept temporally consistent to provide the most accurate comparison between time points (e.g., access to jobs on transit utilizes employment data and transit service from the same period). Base data sources are updated by public agencies at regular intervals. Updates may include new data, fixes to errors, incompleteness, or inconsistencies in legacy data.

2.2. Analysis Methods

A two-prong longitudinal analysis approach was undertaken, including descriptive analysis and inferential change detection modeling. The descriptive and inferential analysis focused on variations in environmental features over time to evaluate the environmental contexts of CPS-3 participants and how they changed over time. Initially, a descriptive analysis approach was employed to examine the distributions of changes in environmental measures across Time 1 and 2. Descriptive analysis included: (1) computation of descriptive statistics, (2) distributional analysis of environmental features, (3) statistical evaluation of mean comparisons, and (4) cross-contingency analysis of walkability levels. The mean changes in environmental features over time were evaluated using paired t-tests, considering the temporal dependence between environmental features measured for the same block groups over time. Mean Δ (difference) and percent change between the mean values (across the sample) over time were computed, and the vectors of mean Δ were then evaluated using paired t-tests. The changes in environmental characteristics over time across spatial and demographic factors were analyzed descriptively and through longitudinal change detection modeling. First, individual-level differences in walkability and constituent-built environment features were computed, and average differences were then estimated across U.S. regions, neighborhood types, age groups, and race groups. Uncertainty measures around the mean estimates (averaged across the individuals) were computed using the Delta method. The resulting statistics were then visualized to gain insights into the evolution of neighborhood physical characteristics across space and demographics. Longitudinal change detection models were developed to simultaneously account for the spatial and demographic factors in

⁵ Each of the four variables was used to rank every block group across the United States. Four separate scores were assigned, one for each of the four variables. The ranking process involved placing all block groups into 20 equal-sized quantiles (each quantile containing 5% of the total) based on the values for each variable (Thomas and Reyes 2024). Each block group was then given a rank from 1 (lowest relative value for a particular variable) to 20 (highest relative value for a particular variable) according to their quantile position. These ranked scores were finally combined through a weighted formula (Frank and Wali 2024, Thomas and Reyes 2024). This standardization approach applied consistently across the two timepoints ensures that any shifts in broader distributions would indicate real changes in built environment metrics over time.

relation to changes in walkability over time (Wooldridge 2010). Model specification testing included specifying the walkability outcome as time-wise walkability in a longitudinal panel and as time-differenced walkability levels in Time 1 and 2. The latter was used considering model significance and interpretability. Regarding exogenous factors, three model specifications were developed: (1) U.S. regions only, (2) U.S. regions + neighborhood types (metropolitan, micropolitan, rural/small town), and (3) U.S. regions + neighborhood types + demographic factors to examine the incremental associations of spatial and demographic factors with expected changes in walkability levels across time. With regards to specification 3, the demographic covariates are those of the participant since our interest lies in estimating how changes in walkability varied across demographic and socioeconomic subgroups. At a simpler level, an ANOVA or ANCOVA could be used, but a longitudinal regression model is preferable since it offers greater flexibility and incorporates simultaneous impacts of multiple covariates more parsimoniously. It also supports more intuitive quantitative interpretation through marginal effects and associated uncertainty bounds. The three specifications were compared using nested likelihood-ratio tests (Koppelman and Bhat 2006) and information criteria-based measures (Bozdogan 2000). Marginal effects and uncertainty bounds were computed at the individual level, averaging over all covariates to interpret the impacts of multiple exogenous factors on expected change in walkability levels (Greene 2003).

3. RESULTS

The results of the empirical analysis are presented in the following order: (1) descriptive analysis of demographic and environmental characteristics, (2) cross-contingency analysis of changes in walkability levels, and (3) longitudinal change detection modeling.

3.1. Descriptive Analysis

Tables 1 and 2 present the descriptive statistics of demographic and environmental variables, whereas Table 3 presents the statistical evaluation of mean comparisons over time. The descriptive statistics shown for demographic variables in Table 1 are for Time 1. Distributions of demographic and regional variables stayed the same between Time 1 and Time 2, except income and marital status (see Table 1 and associated notes). Around 14.9%, 37%, and 46.1% of the participants in Time 1 belonged to [0, \$50,000), [\$50,000, \$100,000], and greater than \$100,000 income groups. The proportion of low-income individuals decreased, whereas the proportion of high-income individuals increased in Time 2 (46.1% in Time 1 vs. 52.8% in Time 2) (see Table 1 and notes). Around 35.3% and 31.9% of the participants in Time 1 possessed a 4-year college degree and a graduate degree, respectively. Participants' marital status also changed significantly over time. The percentage of married individuals or those living with partners increased by around 13.5 percentage points – from 65.6% in Time 1 to 79.1% in Time 2. The prevalence of separated or divorced individuals also increased slightly over time. The sample was predominantly comprised of non-Hispanic white (89.5%), followed by Hispanic (4.9%) and Black (2.2%) individuals. The majority of the sample was comprised of females; only 20.7% of the sample were men. Most individuals (85.3%) lived in metropolitan regions, with another 9.4% and 5.3% living in micropolitan and small town/rural areas. The sample exhibited good representation across the nine U.S. census divisions. As expected, the distributions of race, sex, and spatial variables did not change over time (Table 1).

TABLE 1. Descriptive Statistics of Demographic & Geographic Variables.

Variables	%	Freq.
Demographics & Socioeconomic Factors		
<i>Income *</i>		
[0, \$50,000)	14.95	16322
[\$50,000, \$100,000]	37.08	40471
Greater than \$100,000	46.10	50311
Unknown	1.87	2042
<i>Education</i>		
Up to 2 years college	32.50	35467
4-year college	35.26	38489
Graduate degree	31.92	34839
Unknown	0.32	351
<i>Marital Status *</i>		
Married/living with partner	65.56	71551
Separated/Divorced	7.59	8286
Widowed	1.83	1997
Never married	6.07	6624
Unknown	18.95	20688
<i>Race</i>		
Non-Hispanic white	89.47	97657
Black	2.17	2364
Hispanic	4.89	5338
Other	3.47	3787
<i>Sex</i>		
Male	20.65	22540
<i>Neighborhood type (level of urbanicity)</i>		
Metropolitan	85.31	93114
Micropolitan	9.35	10210
Small town/rural	5.33	5821
<i>Region</i>		
Northeast: New England	4.88	5331
Northeast: Mid Atlantic	15.26	16655
Midwest: East North	22.23	24263
Midwest: West North	9.10	9929
South: South Atlantic	18.50	20187
South: East South	5.97	6514
South: West South	6.16	6728
West: Mountain	5.14	5607
West: Pacific	12.52	13664
Unknown	0.25	268

Notes. SD is standard deviation. N = 109,146 participants. Education data not available for Time 2. The descriptive statistics shown are for Time 1. Distributions of demographic and regional variables are the same between Time 1 and Time 2, except for income and marital status. At Time 2, the percentages of individuals across income categories are as follows: [0, \$50,000) at 12.48%, [\$50,000, \$100,000] at 32.85%, greater than \$100,000 at 52.84%, and unknown at 1.81%. Regarding relationship status, the distribution is: married or living with a partner at 79.05%, separated or divorced at 9.97%, widowed at 3.76%, never married at 6.43%, and unknown at 0.77%. Frequencies across group categories may not sum up to the total sample size due to rounding error.

TABLE 2. Descriptive Statistics of Environmental Variables.

Variables	Time 1				Time 2			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Residential Density								
D1A: Residential density (housing units per acre of unprotected land)	2.14	5.69	0	248.25	2.20	5.86	0	427
D1B: Population density (residents per acre of unprotected land)	4.76	10.45	0	484.62	5.08	16.84	0	3134
Employment Entropy								
5-tier (job types) employment entropy	0.60	0.23	0	1.00	0.61	0.22	0	1.00
8-tier (job types) employment entropy	0.58	0.20	0	0.99	0.59	0.19	0	0.98
Street Connectivity								
D3A: Road network density (road links per sq mile)	11.35	7.91	0	79.07	12.69	8.74	0	83
D3B: Street intersection density (count per sq mile)*	47.39	49.97	0	835.32	48.33	50.68	0	835
Transit Accessibility								
D4a: Distance from population centroid to nearest transit stop (m)	1084	341	0	1250	1042	361	0	1250
Count of transit stops	1.72	5.30	0	329	2.18	4.94	0	150
Car Dependence								
Average annual VMT	27575	3699	6658	40255	30155	4224	0	39979
Walkability								
Walkability index	8.31	3.78	1	20	8.42	3.96	1	20

Notes. SD is standard deviation. N = 109,146 non-movers for all variables across the two time points. * This is a weighted measure. Auto-oriented intersections are removed.

Table 2 shows that environmental features related to urban compactness (residential and population density), diversity (employment mix), urban design (street connectivity), and walkability surrounding CPS-3 participants' home locations exhibited considerable differences over time. To understand the extent of changes, Table 3 presents the magnitude of changes and statistical evaluation of whether the changes over time are statistically significant. Regarding urban compactness, residential and population density measures increased by 2.43% and 6.65% over time, respectively. Results from paired t-tests showed that the mean residential and population densities were statistically significantly different between the two time points ($t = 13.98$ w/df 109145, $p = 0.00$ for residential density, and $t = 8.00$ w/df 109145, $p = 0.00$ for population density) at a significance level of 0.05. Employment entropy also increased over time, indicating an improvement in urban diversity. The five- and eight-tier employment entropies statistically significantly increased by 1.11% and 1.22% between Time 1 and Time 2. As a design measure, street connectivity also improved over time. The count per square mile of pedestrian-accessible intersections increased by 0.939 (or a 1.98% change) between Time 1 and 2. This increase was statistically significant at a 0.05 significance level ($t = 59.38$ w/df 109145, $p = 0.00$). Considerable improvements in transit accessibility were also observed. The distance to the nearest transit stop decreased (indicating better accessibility) by 3.89%. These improvements in the walkability index's constituent-built environment features translated to a considerable improvement in walkability. The index improved statistically significantly by 1.33% (Table 3). These differences were statistically significant at a 95% confidence level.

3.2. Cross-Contingency Analysis of Changes in Walkability Levels

To further understand the covariation between Time 1 and 2 walkability levels, Figure 2 visualizes a cross-contingency analysis showing the conditional distributions of Time 2 walkability on the y-axis across Time 1 walkability levels on the x-axis. The walkability levels in Time 1 and 2 persisted for a majority of the

CPS-3 non-movers. The proportion of individuals who experienced similar walkability levels in Time 1 and Time 2 was considerably higher when the Time 1 walkability level was very low or high. Around 82.3% and 84.5% of participants with very low or high Time 1 walkability experienced similar walkability levels in Time 2, respectively. In comparison, of the participants with low and middle walkability categories in Time 1, only around 55.7% and 55.3% experienced similar walkability levels in Time 2 (Figure 2). Walkability levels in Time 2 improved for around 17.6%, 19.6%, and 23.4% of participants who had very low, low, and middle walkability levels in Time 1, respectively. However, the walkability levels for a considerable proportion of participants also deteriorated over time (Figure 2). These findings provide high-level insights into how walkability levels in Time 2 have persisted or changed conditionally on the full spectrum of Time 1 walkability levels. The forthcoming longitudinal inferential analysis contextualizes some of these changes across spatial and demographic factors.

TABLE 3. Statistical Evaluation of Mean Comparisons Across Time 1 and Time 2 for Environmental Variables.

Variables	Mean Δ (T2 - T1)	% Change	Ha: Mean $\Delta \neq 0$		
			t-statistic	w / DF	p-value
Residential Density					
D1A: Residential density (housing units per acre of unprotected land)	0.052	2.43	13.98	109145	0.00
D1B: Population density (residents per acre of unprotected land)	0.317	6.65	8.00	109145	0.00
Employment Entropy					
5-tier (job types) employment entropy	0.0067	1.11	12.118	109145	0.00
8-tier (job types) employment entropy	0.0071	1.22	15.027	109145	0.00
Street Connectivity					
D3A: Road network density (road links per sq mile)	1.337	11.78	218.60	109145	0.00
D3B: Street intersection density (count per sq mile)	0.939	1.98	59.38	109145	0.00
Transit Accessibility					
D4a: Distance from population centroid to nearest transit stop (m)	-42.187	-3.89	-53.71	109145	0.00
Count of transit stops	0.458	26.60	35.75	109145	0.00
Car Dependence					
Average annual VMT	2580.921	9.36	455.76	109145	0.00
Walkability					
Walkability index	0.111	1.33	18.19	109145	0.00

Notes. Mean Δ is the difference between the mean (across the sample) values of variables in Time 1 (2013) and Time 2 (2020). DF is degrees of freedom. % Change shows the percentage change in mean value in Time 2 with respect to Time 1. Results shown are for paired t-tests considering the temporal dependence between environmental measurements for the same participant (block group) over time.

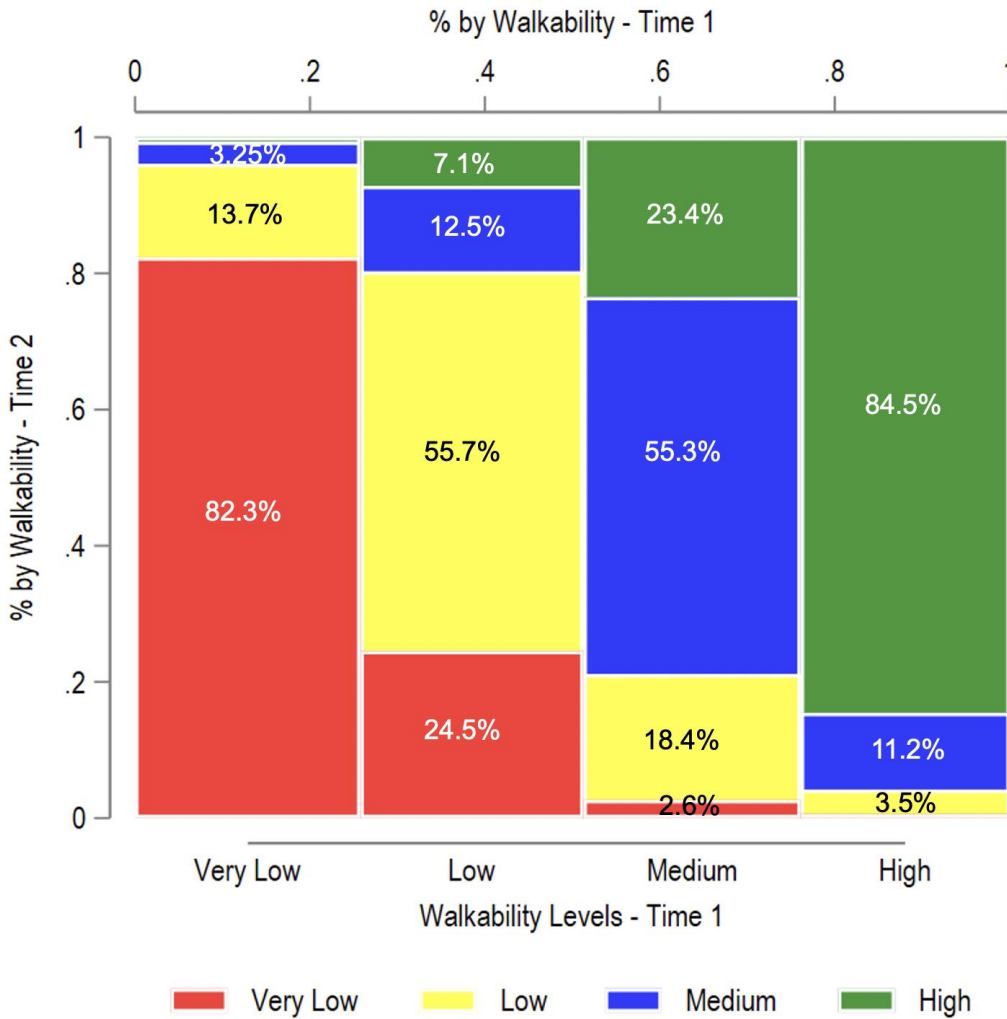


FIGURE 2. Cross-Contingency Analysis of Walkability Levels in Time 1 and Time 2.

Notes. For every category of Time 1 walkability levels (x-axis), the stacked bar chart shows the distribution of Time 2 walkability levels on the y-axis. The following categories are not plotted (as the proportions are very small): Time 2 high x Time 1 very low (0.65%) and Time 2 very low x Time 1 high (0.60%). Walkability levels are defined as very low [0, 25th percentile], low (25th percentile, 50th percentile], medium (50th percentile, 75th percentile], and high (75th percentile, 100th percentile].

3.3. Evaluation of Walkability Changes by Spatial and Demographic Factors

It is also of interest to understand how the changes in walkability vary across demographic, geographic, and socioeconomic characteristics of the participants. Figure 3A shows the distribution of changes in walkability levels between Time 1 and 2 across the nine U.S. census divisions. Walkability on average decreased in the New England, East North, and East South divisions, whereas walkability increased in the remaining six divisions. Among the three divisions experiencing a decrease in walkability, the largest decrease was in the East South division. Related to neighborhood type, walkability increased in metropolitan and micropolitan regions, whereas small towns/rural regions, on average, experienced a decrease in walkability over time (Figure 3B). The average increase in walkability in metropolitan areas was 2.38 times the increase in micropolitan regions. Figures 4 and 5 show the distribution of changes in walkability and built environment metrics (population density, residential density, and pedestrian-accessible intersection density) across age and race groups. Neighborhood walkability index increased the most for older individuals (> 65 years) (Figure 4). The increase in walkability for those aged ≤ 40 years was slightly lower. The lowest increase in walkability over time was observed for participants aged between 50 and 60

years. Regarding individual measures, residential and street intersection densities increased the most for participants aged ≤ 40 years. On the other hand, neighborhood population density increased the most for those older than 65 years (Figure 4).

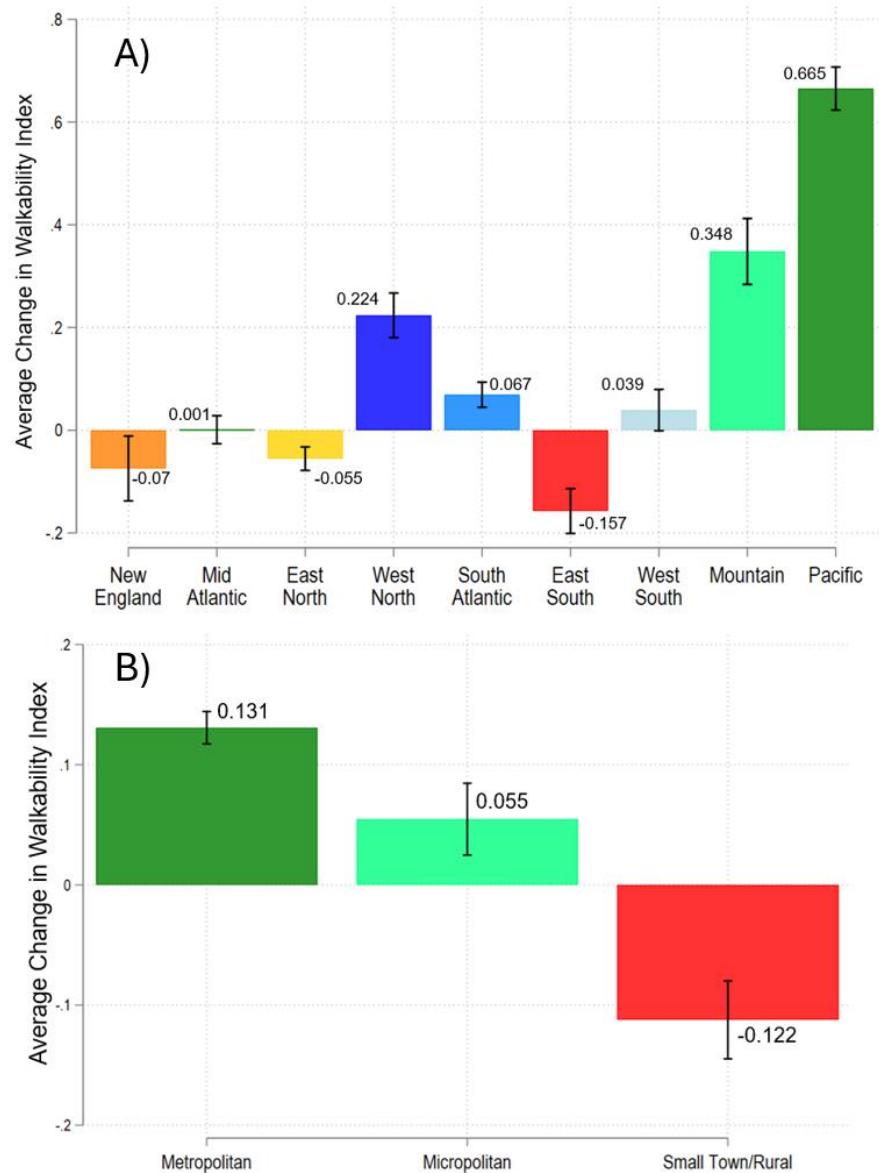


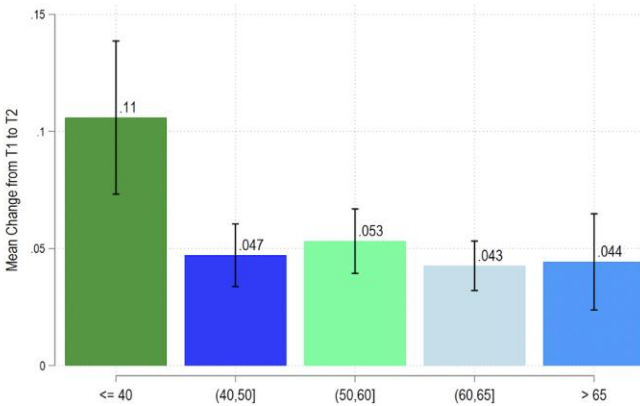
FIGURE 3. Distribution of Changes in Walkability Levels Between Time 1 and Time 2 Across Regions (A) and Neighborhood Types (B).

Notes. Differences in individual-level walkability indices were calculated, followed by computing average change values across neighborhood types. 95% confidence intervals were computed using the Delta Method. Label values show the mean increase/decrease in Time 2 walkability index with respect to Time 1 walkability index. Error bars show estimated 95% confidence intervals.

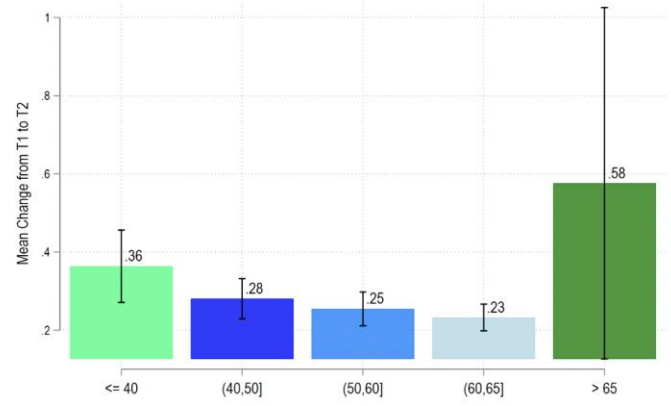
Similarly, walkability measures increased across all race groups, though variations in the magnitude of increase were observed (Figure 5). The lowest increase in walkability index was observed for non-Hispanic white participants. Interestingly, this pattern of lowest increase for non-Hispanic white participants was consistent across residential density, population density, and street intersection density. The increase in walkability was almost similar between the people of color (Hispanic and Black). However, residential density increased more for Hispanic compared to Black participants, whereas the reverse was true for population density.

Change in Key Environmental Metrics by Age Groups

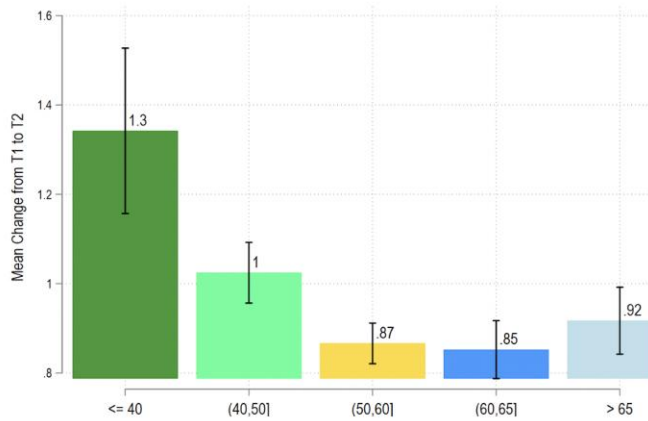
D1A: Residential density (housing units per acre of unprotected land)



D1B: Population density (residents per acre of unprotected land)



D3B: Street intersection density (count per sq mile)



Walkability Index

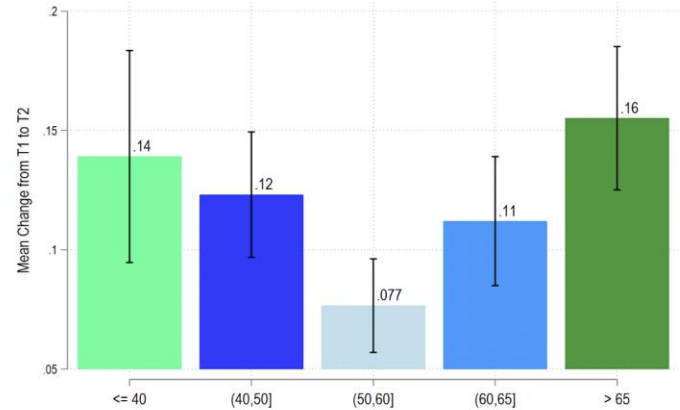


FIGURE 4. Distribution of Changes in Key Environmental Metrics Between Time 1 and Time 2 Across Age Groups.

Notes. Differences in individual-level environmental metrics were calculated by computing average change values across age groups. 95% confidence intervals were computed using the Delta Method. Label values show the mean increase in values of environmental features in Time 2 with respect to Time 1. Error bars show estimated 95% confidence intervals. The bars are colored in order of walkability change magnitude, from green (highest change) to blue to olive teal to yellow (lowest change). (For interpretation of the references to color in this legend, the reader is referred to the Web version of this article.)

Change in Key Environmental Metrics by Race Groups

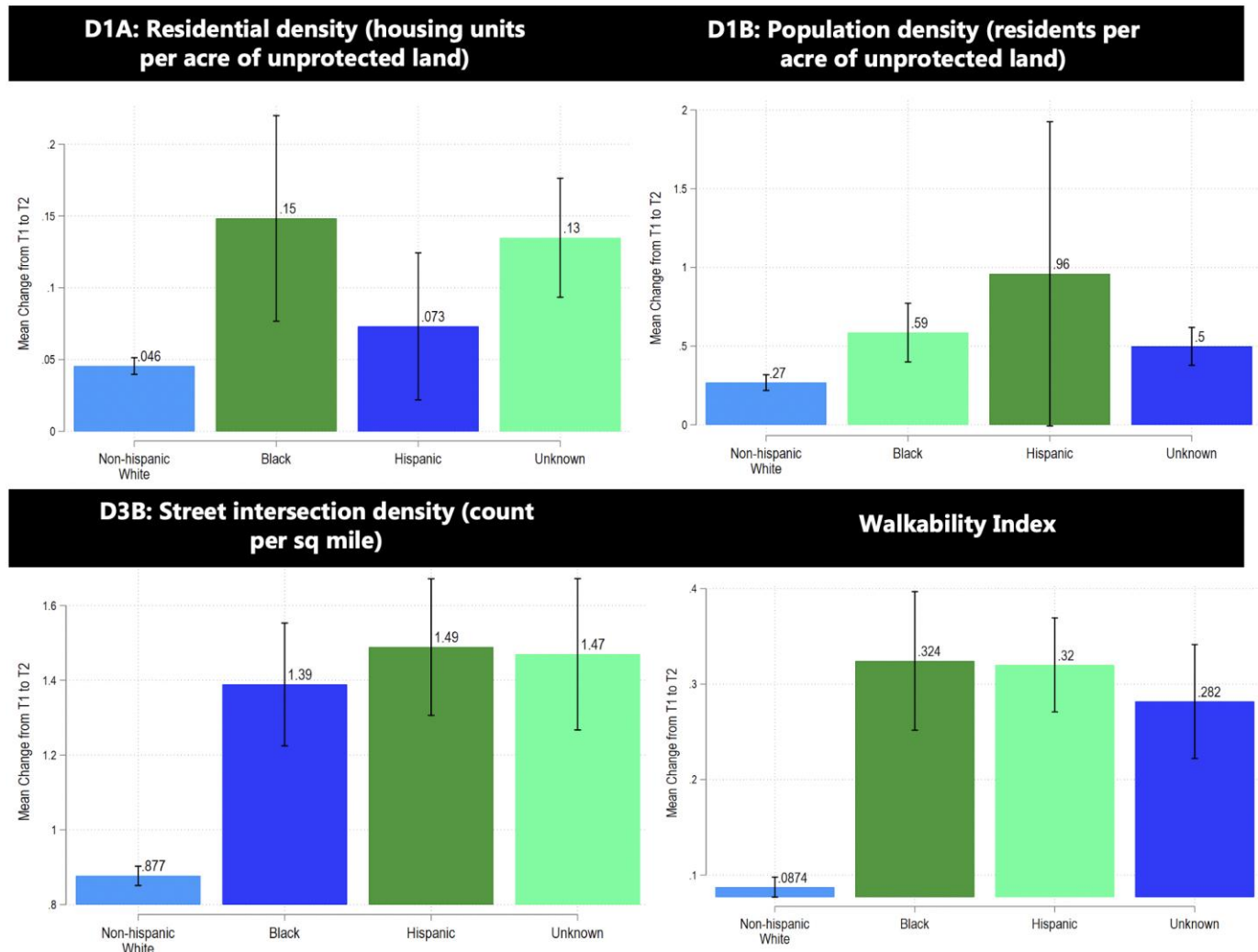


FIGURE 5. Distribution of Changes in Key Environmental Metrics Between Time 1 and Time 2 Across Race Groups.

Notes. Differences in individual-level environmental metrics were calculated by computing average change values across race groups. 95% confidence intervals were computed using the Delta Method. Label values show the mean increase in values of environmental features in Time 2 with respect to Time 1. Error bars show estimated 95% confidence intervals.

3.4. Modeling Results

To simultaneously account for the multiple impacts, Table 4 shows the results of longitudinal change detection models linking the change in walkability with demographic and spatial factors. Foremost, the results of the regression model must not be interpreted causally. The model results do not imply that individuals' demographic factors are causing changes in walkability. Instead, the regression model is correlational, providing insights on how changes in walkability differ across spatial and demographic subgroups.

Compared to specification 1 (only including U.S. regions), the goodness of fit of specification 2 (U.S. regions + neighborhood type) improved significantly. The Akaike Information Criterion for specification 2 decreased by around 43 points. Generally, a difference of over 5 to 10 points between two AICs indicates significant support in favor of the model with the lowest AIC (Anderson and Burnham 2004). The

incorporation of demographic factors in specification 3 further improved the goodness of fit. The AIC of specification 3 decreased further by around 93 units. This suggests that social (demographic) characteristics are correlated with the changes in walkability even after controlling spatial factors. Specification 3 also outperformed the other two specifications in terms of model significance. The log-likelihood at convergence improved the most for specification 3 even after accounting for the additional degrees of freedom implied by the best-fit model containing demographic and spatial parameters. The forthcoming results are based on Specification 3, given its relatively best fit. Confirming the insights obtained from the bivariate descriptive analysis, the models shown in Table 4 capture the relative change in walkability for specific subgroups (e.g., U.S. regions) with respect to the reference group (e.g., New England region). The β coefficients capture the expected (predicted) difference in walkability from T1 to T2 for the corresponding exogenous factor relative to the reference category.

Compared to New England (base), walkability increased over time in all U.S. census divisions except the East South. Walkability change over time was statistically insignificant in the East North division (Table 4). Compared to New England, the predicted walkability change (Time 2 - Time 1 walkability) in the Mountain and Pacific divisions was higher by 0.415 and 0.725 units, respectively (Table 4). On the contrary, the predicted walkability change in East South was lower ($\beta = -0.088$) in comparison to New England. To gain insights into the absolute changes, Figure 6 shows the predicted marginal effects of changes in walkability levels, accounting for the multiple impacts of spatial and demographic factors. On average, walkability increased over time in all US census divisions except East South, East North, and New England (Figure 6). With regards to neighborhood types, the average change in walkability in micropolitan and small town/rural regions over time was lower in comparison to metropolitan regions (base) (Table 4). We note that walkability in micropolitan regions still increased (referring to marginal effects in Figure 6), but the magnitude of increase was lower in comparison to metropolitan areas. Notably, the predicted change in walkability was statistically significantly lower in small town/rural areas (Table 4). Regarding demographic factors, walkability change was lower for all age groups compared to the reference group (> 65 years), although the potential reductions (relative to the reference group) were only statistically significant at the 90% level for the (50, 60] and (60, 65] age groups. We note that walkability improved over time for all age groups (refer to the marginal effects in Figure 6), but the magnitudes of increase across all age groups were lower in comparison to the (60, 65] age group. Finally, with regard to race/ethnicity, walkability increased at a higher rate for Hispanic, Black, and other race participants compared to non-Hispanic White participants (reference group) (Table 4 and Figure 6).

4. DISCUSSION

This study presented a national analysis of the changes in neighborhood environmental features between 2013 and 2020 experienced by participants in the Cancer Prevention Study-3 (CPS-3) cohort. We focused on a geographically and ethnically diverse longitudinal sub-set of over 109,000 participants who did not relocate during the study period and whose residential locations were objectively assessed using block group level environmental data at two time points. This enabled us to examine the evolution of health-related physical environment characteristics of neighborhoods over time being experienced across demographic subgroups within different parts of the nation. It provides a proof of concept that environmental features known as health determinants can be monitored and tracked over time. Changes in environmental features over time were also examined in relation to spatial and demographic factors to understand social and geographic equity in the distribution of walkability and associated characteristics.

TABLE 4. Longitudinal Models of Change in Walkability Over Regions, Neighborhood Types, & Demographics.

Variables	Specification 1: Regions only			Specification 2: Regions + Neighborhood Type			Specification 3: Regions + Neighborhood Type + Demographics		
	β	t-statistic	p-value	β	t-statistic	p-value	β	t-statistic	p-value
Outcome									
Change in walkability index (T2 - T1)	---	---	---	---	---	---	---	---	---
Constant	-0.075	-2.72	0.006	-0.07112	-2.6	0.009	-0.042	-1.36	0.174
Exogenous Factors									
Region									
Northeast: New England (Base)	---	---	---	---	---	---	---	---	---
Northeast: Mid Atlantic	0.076	2.41	0.016	0.085	2.71	0.007	0.078	2.49	0.013
Midwest: East North	0.019	0.63	0.526	0.035	1.16	0.244	0.030	0.99	0.324
Midwest: West North	0.298	8.79	0	0.316	9.28	0	0.313	9.18	0
South: South Atlantic	0.144	4.67	0	0.148	4.82	0	0.132	4.27	0
South: East South	-0.083	-2.24	0.025	-0.071	-1.92	0.055	-0.088	-2.37	0.018
South: West South	0.114	3.1	0.002	0.122	3.33	0.001	0.098	2.68	0.007
West: Mountain	0.423	11.06	0	0.425	11.12	0	0.415	10.86	0
West: Pacific	0.740	22.93	0	0.742	23	0	0.725	22.39	0
Neighborhood type									
Metropolitan (Base)	---	---	---	---	---	---	---	---	---
Micropolitan	---	---	---	-0.029	-1.36	0.174	-0.023	-1.1	0.273
Small town/rural	---	---	---	-0.185	-6.81	0	-0.179	-6.56	0
Demographics									
Age Groups									
≤ 40 years	---	---	---	---	---	---	-0.007	-0.26	0.798
(40, 50] years	---	---	---	---	---	---	-0.024	-1.22	0.223
(50, 60] years	---	---	---	---	---	---	-0.067	-3.72	0
(60, 65] years	---	---	---	---	---	---	-0.037	-1.86	0.064
> 65years (Base)	---	---	---	---	---	---	---	---	---
Race Groups									
Non-Hispanic white (base)	---	---	---	---	---	---	---	---	---
Black	---	---	---	---	---	---	0.286	6.83	0
Hispanic	---	---	---	---	---	---	0.190	6.58	0
Other	---	---	---	---	---	---	0.066	1.98	0.048
Summary Statistics									
N	108,877			108,877			108,877		
Degrees of Freedom	9			11			18		
Log-likelihood	-229,822			-229,798			-229,744		
AIC	459,661.70			459,618.70			459,525.80		

Notes. --- is Not Applicable or Not Included. N is the sample size (i.e., number of participants) available for estimation with complete data on all covariates. Outcome is change in walkability over time (Time 2 – Time 1). AIC is Akaike Information Criterion. Degrees of freedom are the # of estimable parameters.

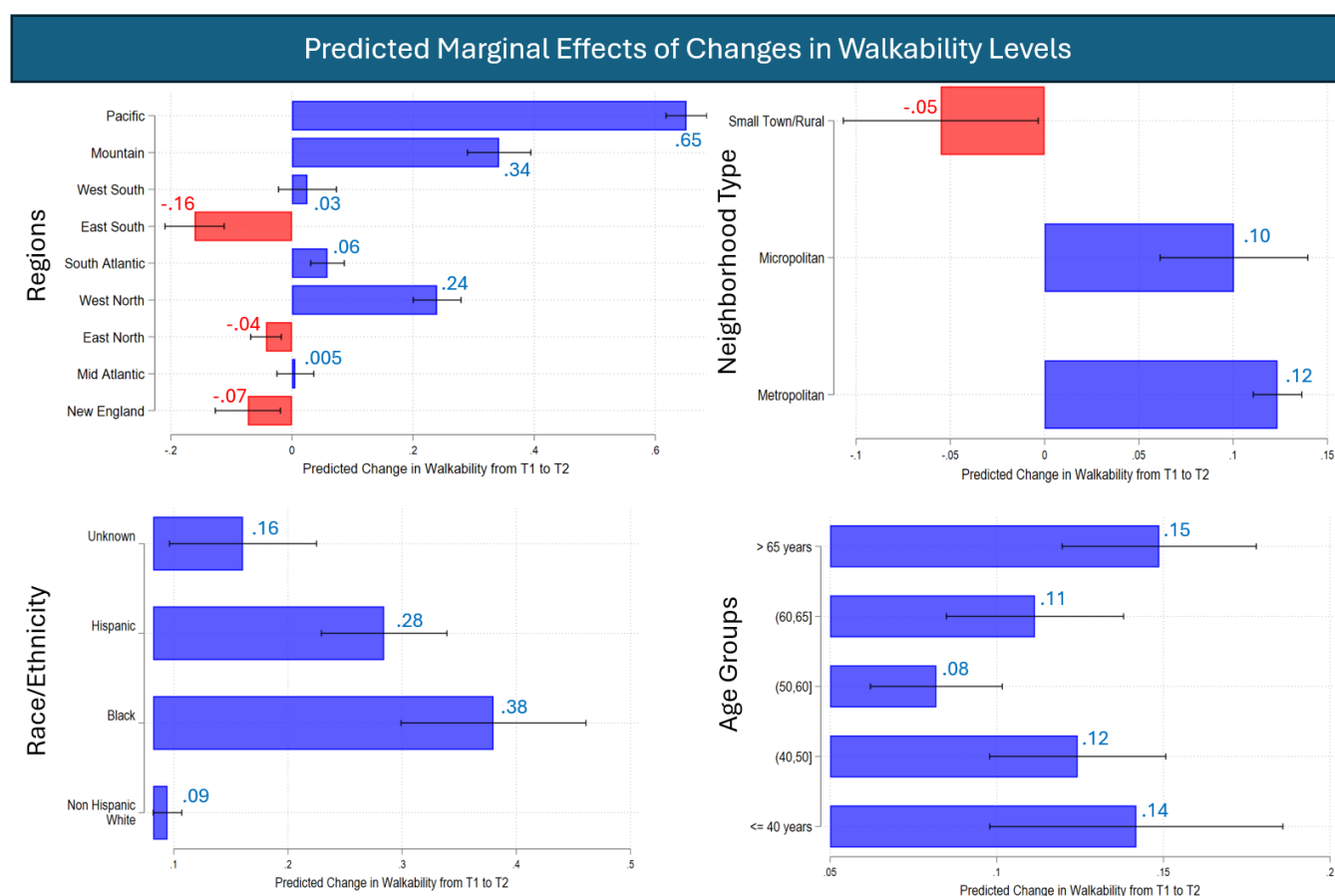


FIGURE 6. Adjusted Predicted Changes in Walkability Over Time Across Regions, Neighborhood Types, Race, and Age Groups.

Notes: The predicted marginal effects are based on the best-fit (specification 3) model adjusting for regions, neighborhood types, race/ethnicity, and age groups. Marginal effects and uncertainty bounds are computed over all covariate values at the individual level and then averaged across the sample.

Foremost, we found significant differences in how the physical characteristics surrounding the home locations of CPS-3 participants have changed over time. A 2.43% and 6.65% increase in residential and population densities (as measures of urban compactness) was observed in the residential neighborhoods of sampled participants. Pedestrian-accessible intersection density (as a measure of street connectivity) also increased by 1.98% over time. These improvements in urban compactness and street connectivity, when combined with the improvements in transit accessibility and employment entropy, resulted in a statistically significant 1.33% increase in the walkability index over time. Overall, the changes in built environment and walkability features around residential locations of non-movers were in the healthful direction⁶. The

⁶ Our focus was on evaluating changes in objectively assessed environmental features for non-movers. However, the parent study sample includes over 39,000 movers, as noted earlier. Separating non-movers from movers within a longitudinal design helps minimize the possibility that the observed changes in environmental characteristics are driven by (often considerable) changes induced by residential relocation (Handy et al. 2005, Ettema and Nieuwenhuis 2017). We also performed pooled and segmented analyses of the changes in environmental characteristics by movers and non-movers (results not shown here). In contrast to the above findings suggesting environmental features changed in the healthful direction for non-movers, the pooled analysis (movers + non-movers) showed that residential density on average decreased by 2.01% over time. Pedestrian-oriented street connectivity also decreased over time by an average of 1.27%. Land use diversity and transit accessibility improved over time though in the pooled analysis. These contrasting changes in pooled analysis led to a negligible increase of 0.25% in neighborhoods' walkability levels over time. The decline in residential density and street connectivity in the pooled sample was unexpected, as the majority

observed changes in environmental characteristics are likely due to infrastructure improvements and investments over time and not from contrived changes due to residential relocation⁷. Compact and walkable neighborhoods with safer pedestrian-oriented infrastructure and greater transit accessibility are associated with greater active travel (MacDonald et al. 2010, Kärmeniemi et al. 2018) and better health outcomes (Stokes et al. 2008, Zapata-Diomedes et al. 2016, Lin et al. 2021). The social and physical fabric of our neighborhoods remains a key context in which health is shaped (Gomez et al. 2015), and the above improvements in the walkability-defining physical environmental characteristics suggest that health gains can be realized over time.

Our results also shed light on the distribution of changes in walkability characteristics over time across spatial and demographic factors for the CPS-3 participants. Longitudinal change detection models provided insights on social and geographic equity in the distribution of changes in walkability. Among the different specifications tested, our results suggested that the combination of spatial (regions and neighborhood type) and demographic factors best correlated with changes in walkability. We posit that demographics are inherently linked with changes in the built environment. For instance, positive changes in walkability would logically attract higher income and more educated residents. Considerable evidence supports this hypothesis (Leinberger 2010, Loh and Leinberger 2019, Oishi et al. 2019). Similarly, areas with higher income and educational attainment are more likely to become more walkable over time, driven by increased economic activity, residential development, and densification over time. These pathways help describe our findings that demographics and spatial factors explain changes in walkability over time, although we emphasize that this relationship is not necessarily causal.

Geographic disparities in the distribution of changes in walkability across U.S. divisions and neighborhood types were observed. Among the nine U.S. divisions, walkability decreased in three U.S. divisions, with the largest decrease observed in the East South division. Nonetheless, the decrease in walkability in the three divisions was only modest. We note that these regional differences are among participants of CPS-3 and may not fully reflect the broader (ecological) patterns of walkability changes in these regions. Rural areas and small towns experienced a reduction in walkability over time, whereas walkability increased in metropolitan and micropolitan regions. Reductions in walkability in rural areas could have occurred due to known population losses or when the new investments made in the sampled CPS-3 neighborhoods did not result in walkability improvements, e.g., building additional road network density that is not pedestrian-accessible or lowered transit accessibility (two constituent measures forming the walkability index measure used). Some population decline may also be occurring in rural areas as people increasingly live in urban areas. These geographical inequities for the CPS-3 cohort are in line with previous studies evaluating spatial variations in walkability characteristics (Jones et al. 2015, Kegler et al. 2015, King and Clarke 2015) and

(73%) are non-movers, for whom density and connectivity would typically remain stable or increase, partly due to the steady growth in housing units and urban infrastructure in recent decades (Statistica 2022). Recent evidence also suggests that urban compactness and street connectivity measures improved over time across U.S. neighborhoods (Frank and Wali 2024). Further analyses revealed that the contradictory findings in the pooled sample were largely driven by movers. For movers, the walkability index in fact statistically significantly decreased by 2.57% over time. These descriptive trends observed for movers are not necessarily unexpected, as individuals may relocate to less walkable areas for various reasons, including aging-related suburban moves. As discussed later, future work should focus on conducting an in-depth inferential assessment of how physical environment characteristics related to walkability have changed over time for movers.

⁷ Despite the increase in walkability, VMT also rose over time, which may seem counterintuitive since improved walkability typically correlates with reduced motorized travel (Ewing and Cervero 2010). However, several factors can help explain the observed trend. The post-recession economic growth from 2010 onwards led to increased overall travel demand and motorized travel (Rafiq and McNally 2021, DOE 2024). Additionally, while urban areas likely witnessed sustainable growth, suburban expansion and urban sprawl also occurred and which may have also contributed to higher overall VMT. Finally, multimodal transportation dynamics may also partly explain this pattern, as improved walkability can coexist with increased VMT in certain contexts, e.g., if people still rely on cars for longer trips or those less suited for walking or biking.

in changes in walkability over time (Frank and Wali 2024). In light of the demographic disparities in physical activity (Whitt-Glover et al. 2009, August and Sorkin 2011) and chronic disease outcomes (Shaw et al. 2016) documented in previous studies, our findings on spatial disparities in walkability can inform future built environment interventions to improve physical activity and overall population health while reducing geographic inequities across communities.

Specific to demographic factors, results imply that walkability improved over time across all age and race groups but exhibited considerable variations. The largest increases in neighborhood walkability were observed for older individuals (> 65 years) and those aged ≤ 40 years. We note that the youngest participant in the CPS-3 subsample was 31 years. Thus, we were unable to examine the potential increase in walkability for younger adults (e.g., age ≤ 30 years). While walkability statistically significantly increased for all race groups, the adjusted longitudinal change detection model showed that the walkability increase was greater for Hispanic, Black, and other race participants compared to the reference group of non-Hispanic white. These results align with past studies suggesting lower walkability levels for majority white and high-income neighborhoods (Conderino et al. 2021). This encouraging finding indicates that built environment investments made during the study period appear to have prioritized vulnerable populations, at least among CPS-3 participants. However, caution is warranted in generalizing this observation, as the sample sizes for people of color in this study, although sizeable, are still considerably smaller than that of non-Hispanic white participants.

4.1. Future Research and Limitations

This is among the first studies to examine changes in finer-resolution physical environment characteristics of participants of a national cohort with sufficient geographic and ethnic diversity. There are several key avenues to expand and build on this work. This study demonstrated the ability to link objectively assessed environmental data at multiple time points with longitudinal health cohort data. This provides the means to connect higher-tier behavioral, environmental, and health and welfare outcomes to the foundational tier of the built environment that we experience in our daily lives. In the future, it would be of interest to analyze how the changes in walkability levels over time correlate with changes in activity patterns and a range of chronic disease outcomes across demographic groups. Future studies should also evaluate longitudinal changes in walkability across additional social indicators, such as socioeconomic factors and across socioeconomic-demographic subgroups. In this regard, integrating broader constructs of social deprivation (such as the social vulnerability index (SVI)) can provide deeper insights on the links between changes in neighborhoods' social and walkability features over time (Flanagan et al. 2011, Wali et al. 2024). It would also be of interest to examine changes in walkability across income and minority subgroups in the most walkable places where minority ethno-racial groups are declining (Bereitschaft 2023). This study focused on non-movers. An in-depth assessment of the ethno-racial profiles of movers in relation to changes in walkability remains an unexplored and promising area for future research. Further, it would be of interest to analyze how residential relocation to neighborhoods of varying walkability levels has impacted activity patterns and health outcomes in the CPS-3 cohort.

Of the 252,404 participants with Time 1 (baseline) survey data, only 65% had follow-up survey data at Time 2. Thus, 35% of the participant sample was discarded. This is a significant sample loss, with unknown data distribution impacts. However, the effective sample size used in this study is still large ($N = 109,146$ non-movers). While we found the CPS-3 cohort to be diverse across age, race, and geography (Patel et al. 2017), the sample is still predominantly comprised of women and non-Hispanic white participants, and great caution must be exercised in generalizing the results of this study to the general U.S. population. Finally, we note that we only had a 7-year window between the Time and Time 2, and the built environment changes slowly. Although we would not expect to observe major changes in a short follow-up period, we observed some considerable changes in the healthful direction. The longitudinal change detection models help document how structural changes in our society differ systematically across demographic groups and are physically manifested in our communities.

5. CONCLUDING REMARKS

This study evaluated how built environmental features have changed over time for participants in a national-level geographically and ethnically diverse CPS-3 cohort. The study provided new insights into the evolution of the physical characteristics of neighborhoods over time and whether the observed changes may support health outcomes. Descriptive and inferential longitudinal change detection modeling revealed modest improvements in urban compactness, street connectivity, transit accessibility, urban diversity, and overall walkability levels in most locations, with some noted exceptions. With an additional focus on geographic equity, potential changes in key built environment and walkability metrics were examined across U.S. divisions, types of neighborhoods by level of urbanicity, and sociodemographic indicators. The results indicated disparities in the distribution of changes in walkability characteristics across U.S. divisions and neighborhood types. The findings on the links between the dynamic spatial patterns of demographics and walkability changes over time can further inform the targeting of interventions for improving neighborhood walkability while reducing geographical inequities and prioritizing the most deprived populations.

6. AUTHOR STATEMENT

CRedit Statement. The authors confirm their contribution to the paper as follows. Behram Wali: conceptualization, methodology, formal analysis, investigation, writing – original draft, writing – reviewing and editing, project administration. Lawrence Frank: conceptualization, methodology, writing – reviewing and editing, project administration. Erika Rees-Punia: conceptualization, writing – reviewing and editing, investigation. Alpa Patel: conceptualization, CPS-3 data acquisition, writing – reviewing and editing. Dr. Patel is the principal investigator of CPS-3 by the American Cancer Society. All authors reviewed and approved the final version of the manuscript.

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9. APPENDIX A

Table A1 provides an overview of the environmental measures that have been joined to the following CPS-3 cohorts: 1) 2006-2013 Baseline, 2) 2006-2013 Enrollment, and 3) the 2018 Survey.

Table A1: Summary of environmental measures joined to the 2013 Baseline, 2013 Enrollment, and 2018 Survey CPS-3 cohorts.

Field Name	Measure Description	Base Data Source	Data Year Release	CPS-3 Alignment	Data Year Alignment
Identifiers					
ID	CPS-3 cohort participant identifier	American Cancer Society	2006-2013, 2018	2006-2013, 2018	2013, 2020
BLOCKGROUP	Census Bureau Federal Information Processing Standards (FIPS) block group identifier (2010) - ACS	Census Bureau	2010	2006-2013, 2018	2013, 2020
GEOID10	Census Bureau Federal Information Processing Standards (FIPS) block group identifier (2010) – UD4H	Census Bureau	2010	2006-2013, 2018	2013, 2020
GEOID19	Census Bureau Federal Information Processing Standards (FIPS) block group identifier (2019 update)	Census Bureau	2019	2006-2013, 2018	2013, 2020
STATEFP	Census Bureau Federal Information Processing Standards (FIPS) state identifier (2019 update)	Census Bureau	2019	2006-2013, 2018	2013, 2020
COUNTYFP	Census Bureau Federal Information Processing Standards (FIPS) county identifier (2019 update)	Census Bureau	2019	2006-2013, 2018	2013, 2020
CBSA	Census Bureau Federal Information Processing Standards (FIPS) Core-based Statistical Area (CBSA) identifier (2019 update)	Census Bureau	2019	2006-2013, 2018	2013, 2020
CBSA_Name	Census Bureau Federal Information Processing Standards (FIPS) Core-based Statistical Area (CBSA) name (2019 update)	Census Bureau	2019	2006-2013, 2018	2013, 2020
Residential Density					
U_D1A_2013	Residential density (housing units per acre of unprotected land)	American Community Survey, 5-Yr. Estimates, U.S. Census Bureau	2013	2006-2013	2013
U_D1A_2020			2018	2018	2020
U_D1B_2013	Population density (residents per acre of unprotected land)		2013	2006-2013	2013
U_D1B_2020			2018	2018	2020
Employment Entropy					
U_D2B_E8MIXA_2013 ^a	8-tier (job types) employment entropy (static 8 employment types) on 0-1 scale	Longitudinal Employer-Household Dynamics (LEHD), U.S. Census Bureau	2013	2006-2013	2013
U_D2B_E8MIXA_2020 ^a			2017	2018	2020
U_D2B_E5MIXA_2013 ^a	5-tier (job types) employment entropy (static 5 employment types) on 0-1 scale		2013	2006-2013	2013
U_D2B_E5MIXA_2020 ^a			2017	2018	2020
Street Connectivity ^b					
U_D3b_2013	Street intersection density (count per square mile, weighted, auto-oriented intersections removed)	Navstreets, HERE Maps	2012	2006-2013	2013
U_D3b_2020			2018	2018	2020

Field Name	Measure Description	Base Data Source	Data Year Release	CPS-3 Alignment	Data Year Alignment
U_D3a_2013	Road network density (all functional class road links per square mile)		2011	2006-2013	2013
U_D3a_2020			2018	2018	2020
Access to Transit ^c					
U_D4a_2013	Distance from population-weighted centroid to nearest transit stop (any mode) in meters	General Transit Feed Specification, Various Transit Authorities	2014	2006-2013	2013
U_D4a_2020			2020	2018	2020
U_TRANSIT_STOP_CNT_2013 ^d	Count of transit stops		2014	2006-2013	2013
U_TRANSIT_STOP_CNT_2020 ^d			2020	2018	2020
Travel Behavior					
U_hh_type1_vmt_2013	Household vehicle miles traveled (VMT) for regional median family income (average annual estimated)	U.S. Department of Transportation, U.S. Department of Housing & Urban Development	2013	2006-2013	2013
U_hh_type1_vmt_2020			2019	2018	2020
Walkability					
U_NatWalkInd_2013	Utilitarian walkability index (residential and employment density, street connectivity, employment entropy, and access to transit)	U.S. Environmental Protection Agency	2013	2006-2013	2013
U_NatWalkInd_2020			2020	2018	2020

Notes:

(a) Eight job classification types were used: 1) retail, 2) office, 3) industrial, 4) service, 5) entertainment, 6) education, 7) healthcare, and 8) public administration. The 5-tier comprises a more aggregated set of sectors: 1) retail, 2) office, 3) industrial, 4) service, and 5) entertainment. (b) Intersection density is derived from the junction points or nodes connecting road segments and quantifies the level of connectivity along the transportation network. Intersection counts are determined by calculating the number of network junctions having three or more road segments intersecting the junction. (c) Network distance to the nearest transit stop of any mode in meters was calculated from the population-weighted block group centroid. Base transit stop data was derived from over 570 transit authorities across the U.S. using the General Transit Specification Feed (GTFS). (d) Counts of all public transit stops include the following modes: 1) commuter rail, 2) metro or subway, 3) light rail and 4) streetcar, and 5) bus. Transit stop locations were spatially referenced using x and y coordinates and spatially selected and counted by block group with all transit stop locations being weighted equally.