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# Comparing residence-based to actual path-based methods for defining adolescents' environmental exposures using granular spatial data

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## Abstract

This paper uses data from a population-based case control study of daily activities and assault injury to examine residence-based versus actual path-based approaches to measuring environmental exposures that pose risks for violence among adolescents. Defining environmental exposures based on participant home address resulted in significant misclassification compared to gold standard daily travel path measures. Dividing participant daily travel paths into origin-destination segments, we explore a method for defining spatial counterfactuals by comparing actual trip path exposures to shortest potential trip path exposures. Spatial methods explored herein can be utilized in future research to more accurately quantify environmental exposures and associations with health outcomes.

## Keywords

adolescent health; violence; environmental exposure; epidemiological methods

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## INTRODUCTION

A growing body of research suggests that where people live and the places in which people spend time may have important impacts on a broad range of health outcomes. In contrast to health predictors such as blood pressure or cholesterol, for which there are clear and objective measurement guidelines, no consensus exists for how best to measure environmental exposures.[1] Failure to appropriately define and measure environmental exposures may lead to misclassification bias, which can impact on the ability to detect meaningful associations between the environment and heath, and can also result in spurious findings.[2–7] Due to budgetary and feasibility limitations, investigators often define environmental exposures based on participant home address.[8,9] Other more nuanced analyses use spatial modeling techniques to study environmental exposures on trips between home and pre-specified destinations.[3] These complex spatial models have been applied predominantly among adult populations to study associations between environmental pollutants and traffic infrastructure on health outcomes.[3,10,11]

Many exposure modeling techniques rely on the assumption that participants will select the shortest potential travel route between a given origin and destination, or that participants are equally likely to select from among available routes based on distance and time constraints.[3,10,11] However, other work suggests that pedestrians select walking paths based on a complex constellation of individual, social and environmental factors, including aesthetic appeal, proximity to retail, traffic patterns, and safety, which ultimately affect their actual walking paths.[12–15] Current modeling techniques are unable to fully account for these complex decision-making inputs, and thus remain vulnerable to misclassification.[11,16]

Even less is known about how travel decision-making may operate specifically among adolescents. Adolescence is a time of tremendous neurocognitive development that directly impacts on risk assessment and decision-making across myriad health behaviors.[17–23] Through cognitive maturation, adolescents develop improved abstract reasoning[17] and refinement of cognitive processing,[20] both of which are important for risk assessment.[18] Most research to understand salient factors in adolescent route choice decision-making has narrowly centered on decisions to walk or bike to school.[24] Perceived safety emerges as a frequent factor of interest, but studies in the general adolescent population demonstrate mixed findings regarding associations between perceptions of safety and walking among adolescents.[24–26] Qualitative research in a sample of Philadelphia youth residing in low resource neighborhoods highlights adolescents' hypervigilance to their immediate surroundings and their focus on strategies to promote safety during daily activities.[27] Further quantitative research that assesses adolescent route choice decision-making in the context of daily activities is needed to inform spatial analysis methods.

Most research that examines the impact of the environment on health relies on observational data because randomized experiments often prove unfeasible or unethical. While statistical methods can account for measured confounding in observational research, techniques to manage unmeasured confounding are limited. This hinders our ability to draw causal inference from observational environmental research, as findings may be due to unmeasured confounding from factors that were either too challenging to measure, or not thought to be important to the associations under study. Researchers have historically employed propensity scores and sensitivity analyses as “proxy counterfactuals” to combat these methodological weaknesses, but these remain vulnerable to unmeasured confounding.[28] Methods for assessing spatial counterfactuals using observational data are urgently needed.

The current study uses data from a population-based case control study of daily activities and assault injury to examine the implications related to using residence-based approaches versus actual travel path-based approaches to measuring environmental exposures that pose risks for violence among adolescents. In doing so, the current study examines the extent to which commonly employed metrics, including home address and shortest potential trip paths, can be used as proxies for a broad range of environmental exposures that adolescents actually encounter during their daily activities, and what factors may influence the accuracy of these predictions. It additionally introduces a method for defining spatial counterfactuals by comparing environmental exposures along actual trip paths selected by youth to exposures that would have accrued had participants chosen to travel the shortest routes to their destinations.

# METHODS

## 1. Overview of Data Source

This study utilized data from control participants in the Space-Time Adolescent Risk Study (STARS), a population-based case control study of daily activities and assault in Philadelphia, PA. That study recruited as cases 10 to 24 year-old males who presented to the Emergency Departments of adjacent pediatric and adult trauma centers with assault-related injuries from 2007–2011. Control participants were recruited using random digit dial in the 12 zip codes that account for the hospitals’ catchment area to achieve population-based sampling and matched on age group strata (10–14, 15–17, 18–24), race, and sex.[29–31] The racial composition of the study sample reflects the fact that in Philadelphia, as in many other urban centers, African American male youth bear a disproportionate burden or violent injury,[32] and therefore represent the majority of cases and matched controls in the larger study, in keeping with demographic trends at the study sites.[33] Because the sample of control participants was recruited to reflect the source population that gave rise to the assault-injured cases in the larger case control study, the control participant neighborhoods represent relatively under-resourced neighborhoods compared to all of Philadelphia.

Participants completed structured in-person interviews during which the trained interviewer collected a detailed record of each participant’s daily activities. For control participants, this involved recounting details for a recent day (within 3 days of the interview, randomly assigned). Using a customized version of ArcEngine software, the participants “walked the interviewer through” their entire day from awakening until going to sleep. With a stylus, the interviewer placed points on the interactive map to draw the participant’s path, which were automatically coded with latitude and longitude coordinates. After processing, the data record consisted of many rows per participant with each row being a 1 minute interval that denoted where the participant was, what they were doing, their mode of transit, and who they were with. Additional details related to study design and daily travel path data collection have been previously reported.[34] The study was approved by the Institutional

Review Boards of the University of Pennsylvania and The Children's Hospital of Philadelphia.

Utilizing data from control participants in the STARS afforded a unique opportunity to examine multiple methods for quantifying environmental exposures for violence encountered in the context of daily activity among a population-based sample of Philadelphia youth. The study enrolled 283 adolescent male control participants, of whom 274 provided detailed daily path data. The participant daily paths traversed a median distance of 4.8 miles and included a total of 1,590 self-powered trips.

## 2. Measuring Environmental Exposures

We gathered data on 19 environmental variables of interest from 2010 Census data (median household income, per capita income, unemployment, college education, racial and ethnic composition, population density, adolescent population density, household alcohol expenditures; census block group (BG)), the City of Philadelphia (fire stations, police stations, recreation department facilities; point location), the Pennsylvania Liquor Board (alcohol outlets; point location), the Department of Education (truancy rate; BG), and the University of Pennsylvania Cartographic Modeling Lab (CML) (vacant properties, crimes (vandalism, disorderly conduct, public drunkenness, narcotics arrests), and murals; point location).

We additionally included 5 items measuring neighborhood resident cohesion (belonging, improvement, help, trust, participation; census tract (CT)) and 3 items measuring neighborhood stress and violence exposure (stress, violence victimization, firearm access; CT) from the 2010 Philadelphia Health Management Corporation's Southeastern Pennsylvania Household Survey (PHMC), a bi-annual survey of 10,000 households in the region.[35] Questions that used ordinal response scales were recoded into dichotomous outcomes and summarized as the proportion coded 1 per census tract (Supplementary Table 1).

We ascribed participant exposure to environmental risk factors for violence using three methods: residence-based measurement, daily travel path-based measurement, and trip path-based measurement (origin-destination segments of the full path). Next, we compared residence-based to daily travel path-based measurements. Lastly, we compared two forms of trip path-based measurements to examine differences between actual routes and shortest potential routes between origin-destination segments.

**1) Residence-Based Measurement—**Each environmental variable was geographically referenced with a pair of latitude and longitude coordinates (either explicitly for points or as a geographic centroid for polygons), which were subsequently converted to raster map layers using kernel density (City of Philadelphia, Pennsylvania Liquor Board, Department of Education, CML) and inverse distance weighting (Census, PHMC) calculations. Raster layer calculations employed default bandwidths in ArcGIS that use the spatial distribution of each variable (e.g. locations of all vacant properties within Philadelphia county) to determine the search radius and define the level of environmental variables at each point across the entire Philadelphia landscape.[36] Using kernel density and inverse distance weighting measures, which are continuous and boundary-free, avoids inappropriate aggregation effects.[37] These methods create smooth surface layers that can more accurately ascribe environmental exposures to given participant path locations than using arbitrary boundaries such as census tracts. To define residence-based environmental exposures, participants were assigned unique exposure measures to each of the 27 environmental variables of interest based on the raster map layer values at their home address latitude and longitude coordinates.

**2) Daily Travel Path-Based Measurement—**Participants' detailed minute-by-minute daily travel paths were overlaid on the Philadelphia landscape to calculate environmental exposures encountered in the context of daily activities. Using the same kernel density and inverse distance weighting raster map layers described in the residence-based measurement, we assigned unique exposures to each of the 27 environmental variables using the latitude and longitude coordinates of each daily path point. Based on the data collection method employed, daily path points were one minute apart, with the distance between path points being a function of participant travel speed. We subsequently calculated the mean exposure to each environmental feature across the participants' entire daily travel path by dividing the sum of all exposure point values by the number of path points. Calculating the mean exposure across the entire daily travel path allowed for the direct comparison of residence-based and daily path-based environmental exposure measures.

**3) Trip Path-Based Measurement—**In the trip path-based measurement, we took a different approach to analyzing the GIS travel path data to better understand the routes that participants selected to travel between origins and destinations. For this analysis, we divided participants' entire daily travel paths into a series of multiple trips. Each trip included an origin, defined as the starting location, the intervening travel path points, defined as the point locations demarcated in 1 minute intervals, and a destination, defined as the end location. For example, a trip started at a participant's home (origin), traversed five blocks (ten intervening path points, each one minute apart), and ended at the participant's school (destination). To accomplish this GIS data reconfiguration, we first used participant free-text descriptors to identify time-points at which participants switched activities (e.g. "getting ready for school" followed by "walking to school") to define a trip. We next eliminated any trips that traversed less than 10 feet, as these represented very little geographic movement and were unlikely to reflect trips with multiple possible routes to choose from. Because adolescents have the most personal agency in selecting a travel path while using self-powered modes of transit (as opposed to pre-determined public transit routes, or when they are passengers in vehicles), we limited the trip path analyses to trips that occurred using ≥90% self-powered modes of transit (on foot, bicycle).

We next used ArcGIS 10.3.1 to delineate the actual trip paths, defined as the actual routes that participants traveled to get from a given origin to a given destination and the shortest potential trip paths, defined as the shortest walking route between a given origin and destination. To delineate actual trip paths, we input the origin, all 1-minute-interval intervening path points, and the destination. To calculate shortest potential trip paths, we input only the origin and destination. We then used the ArcGIS Network Analyst feature with the NAVTEQ StreetMap Premium for ArcGIS – 2012 map layer to determine the shortest possible walking route between each origin and destination. We selected the NAVTEQ StreetMap due to the presence of sophisticated features that allowed us to specify routes where pedestrians were allowed to walk (i.e. no highways would be included). The map layer does not allow for specification of bicycle routes. However, results from sensitivity analyses restricted to only on-foot trips were consistent; thus both walking and biking routes were combined for analysis.

We subsequently calculated measures of exposure to environmental features in the immediate surroundings of the actual and shortest potential trip paths to differentiate on a very granular scale differences in environmental exposures along each path. Standard kernel density and inverse distance weighting methods of ascribing exposures are not well suited to assessing differences between two short paths in close proximity. For this reason, we utilized a different approach for these comparisons.

For environmental features for which we had point-based data (vandalism, narcotics arrests, disorderly conduct, public drunkenness, alcohol outlets, vacant properties, recreation centers, and murals), we created distance buffers around the actual trip paths and shortest potential trip paths. We used two distance buffers: 1) 60ft buffers and 2) 660ft buffers. These distances were selected to reflect exposure to environmental features on either side of the street that participants walked down (60ft) and to capture exposures within a city block of each trip path (660ft) and are consistent with distances employed in prior research.[38,39] We calculated cumulative exposures along each actual and shortest potential trip path in ArcGIS by summing the environmental exposure points that intersected each 60ft and 660ft buffered trip path. We also calculated exposure density, defined as the exposure per 1,000ft traversed along each path. We postulated that exposure density was the most clinically-relevant measure because it tends to be reflective of "hot spots" where these environmental risk factors cluster.[34,40]

For environmental features for which we had polygon-based data (Census, PHMC), we calculated a weighted mean exposure across all of the polygons that each actual and shortest potential trip path traversed. To accomplish this, we measured exposures at each origin and destination point, and every 50 feet along the actual and shortest potential trip paths. Exposure at each of these points was defined by the value of the underlying environmental feature polygon (e.g. census block group) at the latitude and longitude coordinates. We then calculated a weighted average across all of the exposure values contained in a given trip path. For example, if an actual trip path spanned 350 feet, we obtained exposure measurements at the origin (0 feet), six intervening path points (every 50 feet), and the destination (350 feet), and used all eight points to calculate the weighted average exposure.

## 3. Statistical Analysis

**1) Descriptive statistics—**We calculated means and standard deviations of exposures to all 27 environmental variables at participants' home addresses (residence-based measure) and along participants' entire daily travel paths (daily travel path-based measure). We also calculated z scores to standardize mean exposures to facilitate graphical comparisons across variables. We used the one sample z score formula for each calculation: $z = (x - \mu)/\sigma$ where μ is the mean of the environmental variable in our study population and σ is the standard deviation.

**2) Comparing residence-based measures to daily travel path-based measures—**We conducted t tests to assess for statistically significant differences between residence-based and daily travel path-based values for each of the 27 environmental variables. Next, we used ordinary least squares (OLS) regression to calculate how much of the actual environmental exposures accrued during daily activity (gold standard) could be explained by the residence-based measurement for each of the 27 environmental variables. The independent variable in each of the 27 crude regressions was the participant exposure as measured at the home address location. The dependent variable was the mean exposure experienced by each participant across his entire daily travel path. We reported the R squared value for each crude regression model. We also generated separate scatterplots for each standardized environmental variable to visually display the relationship between these two methods of exposure calculation.

**3) Comparing actual trip paths and shortest potential trip paths—**Methods for comparing the actual trip paths that participants selected (e.g. path between a restaurant and a friend's house) to the shortest potential trip paths differed based on whether environmental exposure variables were available as points or polygons. For environmental variables with point-level data, we calculated, within each subject, for each set of origin and destination points, the difference in cumulative exposure between the shortest potential trip path and the actual trip path: (*difference in cumulative exposure* = shortest potential trip path cumulative exposure – actual trip path cumulative exposure). We also calculated the difference in the exposure density between the actual and shortest potential trip path pair by subtracting the actual trip path exposure per 1,000 feet traversed from the shortest potential trip path exposure per 1,000 feet traversed (*difference in exposure density*). Differences in cumulative exposure and exposure density were calculated using both 60ft and 660ft buffers. For environmental variables with polygon-level data, for each actual and shortest potential trip path pair, we calculated the difference in the weighted mean exposure to each of the polygon-level environmental exposures of interest by subtracting the actual trip path weighted mean exposure from the shortest potential trip path weighted mean exposure (*difference in mean exposure*). Under all three calculations, any differences >0 represent instances in which the exposure along the shortest potential trip path exceeds the exposure along the actual trip path.

Data were analyzed at the subject level. The difference values across all of a given participant's trips were averaged such that all trips contributed equally to the mean calculation. We calculated regression coefficients, 95% confidence intervals, and p values for intercept-only models for each environmental variable using OLS regression. Intercept-only models allowed us to determine whether the observed differences between environmental exposures along actual and shortest potential trip paths were statistically significant. We additionally ran a trip-level analysis using the individual trip pairs as the unit of analysis. In these models, we used xtreg and accounted for clustering of trips within study participants. After excluding several outliers with trip numbers >2 standard deviations above the mean, results were identical to the subject-level analysis (data not shown). Analyses were conducted using STATAv15 (College Station, TX). Tests of statistical significance were two-tailed and $p<0.05$ was used as the threshold for significance.

# RESULTS

## 1. Characteristics of participants

We enrolled 283 adolescent male control participants. Median participant age was 18.6 years and 98% were African American (Table 1). Almost all youth less than 18 years of age and slightly less than half of youth ages 18 or older were currently enrolled in school and a third were currently working. Participants reported high levels of prior violence involvement and witnessing violence. Three quarters endorsed ever changing their travel route based on safety concerns, with 18% doing so on a daily basis and an additional 20% doing so on a weekly basis.

## 2. Characteristics of activity paths

Of the 283 enrolled control participants, 274 provided detailed daily path data and comprised the daily travel path analysis sample. Median daily travel path duration was 7.6 hours (IQR: 3.8 −11.7). Median distance traversed across the entire daily travel path was 4.8 miles (IQR: 1.7–11.7). Entire daily travel paths were divided into origin-destination segments to define trip paths (e.g. trip from home to school) (Figure 1). There were a total of 2,539 trip paths that covered more than 10 feet across all 274 participants. Of these, 1,590 trip paths involved ≥90% self-powered travel (on foot, bike), which comprised the trip path analysis sample. The median number of trips per participant was 7 (IQR: 4–11). Mean trip path length was 0.47 miles (SD 1.51) and median trip path length was 0.19 miles (IQR: 0.08–0.45).

## 3. Environmental characteristics at home address

Figure 2 depicts participants' home address locations, which have been randomly jittered to protect confidentiality. Neighborhood median household income was $25,963 at the home address locations of participants, considerably below the median household income of $32,248 across all Philadelphia neighborhoods (Table 2).[41] The unemployment rate was 83 per 1,000 residents. Narcotics arrests and vandalism rates were 315 and 299, respectively.

## 4. Environmental characteristics across entire daily travel paths

Figure 3 depicts participants' daily travel paths overlaid on the kernel density distribution of vandalism locations as an example. Reflected in the multiple peaks and valleys, the concentration of vandalism varies widely across the Philadelphia landscape. Additionally, the overlaid daily travel paths demonstrate that participants traversed this variable exposure terrain in the context of their daily activities. Similar patterns emerged across the other 26 environmental exposures of interest. The mean per capita income in neighborhoods that participants traversed was $13,352 (Table 2). On average, approximately 237 per 1,000 residents had received some college education across the neighborhoods that participants traversed.

### 5. Comparing residence-based measures to daily travel path-based measures

Table 2 presents the results of t tests comparing mean exposures for each of the 27 environmental features defined by home address-based measures versus daily travel path-based measures. In these comparisons, using home address-based rather than entire daily travel path-based methods resulted in statistically significant differences in mean environmental exposure to demographic factors (per capita income, per capita college education, per capita Black residents), crimes (vandalism, narcotics arrests, disorderly conduct, public drunkenness), structural features (alcohol outlets), measures of resident cohesion (trust among neighbors), and measures of neighborhood violence and weapons (violence victimization, and firearms in/around homes) (Table 2).

R squared values reflect the degree to which home address exposures explain the environmental exposures experienced by youth in the context of their entire daily travel path. R squared values demonstrate variability across the 27 environmental exposures. For neighborhood demographic characteristics, R squared ranged from 0.37 for per capita unemployment to 0.78 for per capita Hispanic residents. For crime variables, R squared ranged from 0.23 for public drunkenness to 0.65 for narcotics arrests. Among structural features, R squared ranged from 0.39 for alcohol outlets to 0.63 for vacant properties. Regarding the measures of resident cohesion, R squared ranged from 0.64 to 0.79. Figure 4 depicts a scatterplot comparing the standardized (z score) exposure to vacant properties measured at each participant's home address versus across his entire daily travel path. Notably, while z scores were similar for some study participants across the two measurement methods, other participants' z scores differed by more than 2 standard deviations. Graphs of the remaining 26 environmental variables depicted similar patterns (Supplementary Figure 1).

### 6. Comparing actual to shortest potential trip paths

The median number of trips per participant was 7 (IQR: 4–11). Mean actual trip path length was 0.47 miles (SD 1.51) and median actual trip path length was 0.19 miles (IQR: 0.08–0.45). Mean and median shortest potential trip path length were 0.26 miles (SD 0.42) and 0.14 miles (IQR: 0.05–0.32), respectively.

Figure 5 depicts actual trip paths and shortest potential trip paths overlaid on the location of narcotics arrests in 2009 and demonstrates participants often selected actual trip paths that differed from the shortest potential trip paths. There were statistically significant differences in cumulative exposure and exposure density between the environmental exposures accrued along actual trip paths compared to the shortest potential trip paths for several point-level variables (Table 3). Cumulative exposure to vandalism, narcotics arrests, disorderly conduct, public drunkenness, and murals were all significantly higher along actual trip paths compared to shortest potential trip paths, as reflected by beta coefficients <0 when paths were compared using both 60ft and 660ft buffers. Cumulative exposure to vacant properties and recreation centers was significantly higher along actual trip paths using a 660ft buffer. Relatively fewer differences in exposure density, which we postulate to be the more clinically meaningful exposure to "hot spots" of environmental risk factors for violence, reached statistical significance. However, exposure density was significantly higher along the shortest potential trip paths for disorderly conduct using both 60ft and 660ft buffers. Exposure density was also significantly higher along the shortest potential trip path for vandalism using a 60ft buffer and for narcotics arrests using a 660ft buffer. The beta coefficients for public drunkenness, vacant properties, recreation centers, and murals were also >0, demonstrating point estimates wherein exposure density was higher along the shortest potential trip path than the actual trip path using both 60ft and 660ft buffers, but these did not reach statistical significance.

There were no statistically significant differences in the weighted mean exposure along actual trip paths compared to shortest potential trip paths for environmental exposures for which polygon-based measures were employed (Table 4). The majority of the beta coefficients, especially those comparing differences in mean exposure for measures of resident cohesion, stress, and violence exposure clustered around zero.

## DISCUSSION

Using a unique opportunity afforded through a recent population-based case control study of adolescent males in Philadelphia, we compared multiple different approaches to defining exposure to environmental risk and protective factors associated with assault injury. We first defined environmental exposures based on the location of participants' homes. We then calculated environmental exposures using detailed daily travel paths that recorded the precise locations participants encountered in the course of their daily activities. In comparing residence-based measurement and daily travel path-based measurement, we found that home address location explained only part of the exposures experienced by participants in the course of their daily activities. The amount of variability explained by residence-based measurement varied a lot across the different environmental exposures (R squared range: 0.26–0.79).

These findings are in keeping with prior research which demonstrates that participants travel well beyond their immediate home surroundings in the context of daily activities.[10–12,42] This suggests the need for research to continue to assess youth's detailed daily travel paths in order to capture the most accurate assessments of environmental exposures, despite associated costs and complexities.[2] A detailed spatial data collection approach will ultimately advance the field of injury science by allowing more accurate and precise estimates of the associations between environmental exposures and injury outcomes.

The current analysis highlights how selecting among different methods for ascribing environmental risk factors to adolescent participants can result in significant differences in exposure estimates. Simply defining environmental exposures based on participant home address can fail to fully account for individual variability in exposure levels accrued over daily activity and did fail in the study we have described here. The degree of mismatch varied across environmental factors and likely reflects a combination of the underlying exposure distribution across the study area and the variable mobility of participants. For environmental exposures that are relatively homogeneous and/or when participants do not venture far from home, assigning exposures based on home address may serve as a reasonable proxy. However, when tremendous variability in environmental exposures exists across the landscape and/or participants cover a large terrain, residence-based estimates are unlikely to capture individual-level exposures experienced during daily activities.[12]

The degree to which the home address exposure explained variability in actual path exposure did not appear to be related to the granularity of the underlying environmental data; R squared was highly variable across environmental features that were measured at the point-level, census block group-level and census tract-level when kernel density and inverse-distance weighting was used to assign exposures to participants. This finding suggests that even in instances where environmental variables are only available at aggregated areal units, collecting detailed travel path data may nonetheless provide more accurate exposure profiles than residence-based measurement.

We also proposed a novel use of detailed daily travel path data to study how route choice impacts environmental exposures in participants' immediate surroundings. In this method, we divided each participant's entire daily travel path into a series of trips defined by origins and destinations. We compared the exposure in the immediate vicinity of the actual trip path taken by the participant to the exposure that each participant would have accrued had they chosen to take the shortest potential route between the origin and destination. Consistent with prior research, we found that participants often selected routes that differed from the shortest potential trip path.[13,16] For point-level data, we found statistically significant exposure differences between the actual trip paths and shortest potential trip paths across both 60ft and 660ft buffers.

We found that participants tended to select actual routes which avoided high density "hot spots" for several important environmental risk factors for violence including vandalism, disorderly conduct, and narcotics arrests. These findings are consistent with participants' reports on the survey of frequently changing their routes based on safety concerns. Avoiding "hot spots" of environmental risk factors is in keeping with prior qualitative research with a similar population, which demonstrated the salience of safety concerns in travel decisions.[27] The trip path analysis thus provides some preliminary quantitative evidence to suggest that adolescent males may actually be selecting travel routes in urban Philadelphia neighborhoods at least in part due to safety concerns.

We found this method of comparing actual and potential trip paths to be most useful when environmental feature data was available at the point-level. Thus, in circumstances where granular, point-level exposure data is available, this method can detect significant differences in the distribution of environmental risk factors in the immediate surroundings of participants. However, when environmental feature data is only available as larger area polygons (e.g. census block groups), this spatial counterfactual method is less likely to yield meaningful information because actual and shortest potential routes often cross through similar or identical polygon values. Under these circumstances, environmental exposure data lacks the spatial resolution to properly differentiate exposures in the immediate vicinity of actual versus potential trip paths. Additionally, for environmental risk factors for violence, adjacent polygons tend to have similar characteristics because factors such as crime and vacant properties tend to cluster in neighborhoods. For other types of environmental exposures where values differ more dramatically across adjacent polygons, the spatial counterfactual method may still be useful in appreciating differences across larger area polygon-level exposures. Using inverse distance weighted calculations to create narrow bandwidth kernel density plots surrounding individual activity paths may improve the ability to differentiate exposures to polygon-level variables across actual versus shortest potential trip paths.

Dividing detailed daily travel paths into series of origins and destinations holds promise as an innovative approach for defining spatial counterfactuals. It provides an opportunity to work around unmeasured confounding, which poses a potential threat to the validity of observational spatial research. The trip path-based measurement method asks, what would a participant have been exposed to if, instead of traveling along their actual selected trip path, they chose to travel along the shortest possible path between their origin and destination? Under this type of analysis, each participant serves as his own control, thereby balancing both measured and unmeasured confounders. The approach detailed herein, which compares actual trip paths to shortest potential trip paths, outlines a method for exploring travel decisions. While shortest potential trip path is the most computationally straightforward counterfactual in ArcGIS, other counterfactuals such as illumination, walkability score, or traffic congestion could also be employed. Considered broadly, this method can be used to ask whether participants are going out of their way to avoid certain environmental risk factors, or to seek out environmental protective factors.

## LIMITATIONS

This study has several important limitations. It relies on data from a single population-based case control study of adolescent males between the ages of 10 and 24, which was originally conducted to study the impact of daily activities on risk of assault injury. The study was conducted in Philadelphia and results may not translate beyond the current geographic location. Additionally, due to population-based sampling from a limited catchment area (12 zip codes), which tends to reflect less affluent neighborhoods within Philadelphia, the results may not be generalizable to other sections of the city.

Second, the study focused on the presence of statistically significant differences among the various exposure methods. Since no consensus exists for what constitutes a clinically significant difference in exposure to environmental features such as narcotics arrests or vacant properties, the authors purposely avoided drawing such conclusions. However, this knowledge gap regarding what constitutes a clinically significant exposure does not detract from the utility of employing granular methods to accurately ascribe environmental exposures. Applying granular measures can ultimately lead to discovery of clinically-meaningful dose-response or threshold effects between environmental features and violence. The scale at which it is reasonable or ideal to measure information for a given study will depend on the nature of the exposure and the outcome and the relationship between the two. Conceptual frameworks can inform what type of measurement approach will be appropriate and sufficient to collect accurate exposure data without unnecessary expense. The current study offers evidence that using granular measures of environmental exposures is important for adolescents, a population for which relatively less daily travel path and health outcomes research exists.

In regard to the methods proposed to assess spatial counterfactuals, only one form of impedance (shortest potential trip path) was considered. Results may differ if alternative impedance metrics are employed. However, shortest potential trip path was selected as this metric is commonly used in environmental exposure research and spatial analysis modeling.[3,10,11] Future simulation analyses can better elucidate which environmental features may be adequately accounted for using home address as a proxy and which require more detailed daily path data to guide future studies of the association between environmental exposures and health outcomes among adolescents.

The study purposely employed several different strategies to ascribe environmental exposures to participants. It is possible that some of the observed differences could be due to the use of different methodological approaches, rather than true differences in participant exposure. Distinct methods were selected based on the granularity of the environmental exposure data and the scale of the participant GIS data under each set of conditions. Importantly, comparisons were only made between exposure estimates that used the same methods for ascribing exposures (e.g. kernel density). Because of methodological differences, comparisons should not be drawn between residence-based and trip path-based estimates, nor between daily travel path-based and trip path-based estimates. However, each approach contributes unique information to enhance our understanding of how methodological decisions can significantly impact environmental exposures ascribed to participants.

## CONCLUSION

Using data from a population-based case control study of daily activities and assault, we characterized participant exposure to environmental risk factors using three different methods: residence-based, daily travel path-based, and trip path-based measurement. We found that residence-based measurement only partially explained individuals' exposure to environmental features across their entire daily travel paths. Additionally, we found that participants' actual trip paths often differed from shortest potential trip paths, and resulted in statistically significant differences in exposure to point-based environmental features. Methods proposed herein provide a framework for assessing spatial counterfactuals which can be applied to future injury research. Future simulation work should study how the distribution of environmental features and participant activities across the landscape impacts observed associations in order to inform best practices in environmental exposure measurement among adolescents.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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## HIGHLIGHTS

- Examines residence vs. path-based approaches to measure environmental violence risks
- Home address resulted in significant misclassification compared to daily paths
- Trip path analyses provided a method for generating spatial counterfactuals
- Proposed actual path-based methods can be applied to future injury research

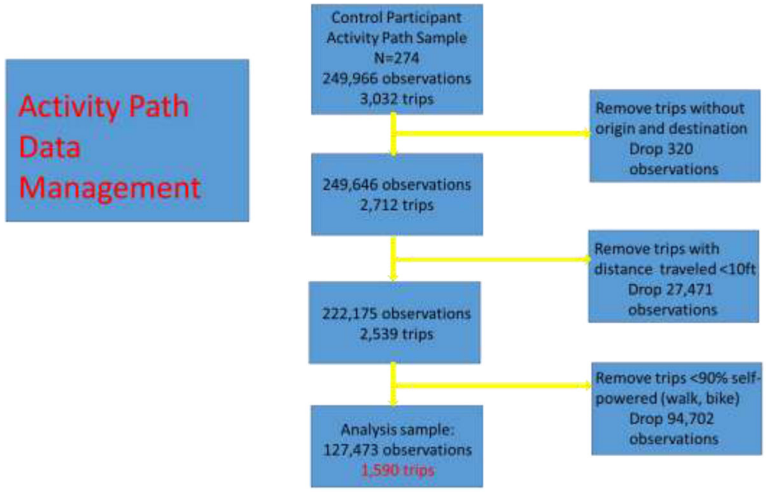


**Figure 1.**
Activity path data management

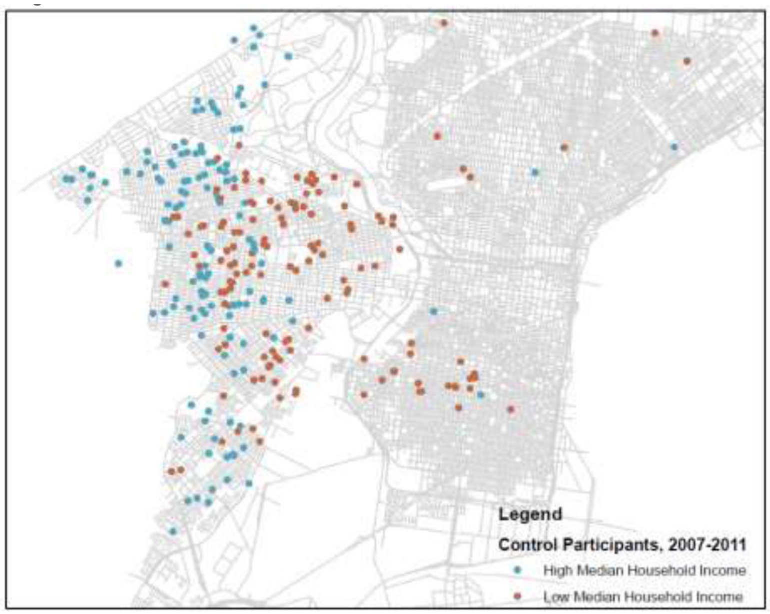


**Figure 2.**
Control participant home address locations, by level of median household income in neighborhood
*all participant locations have been jittered by a randomly assigned distance between 200 and 1200ft in both latitude and longitude to protect participant confidentiality

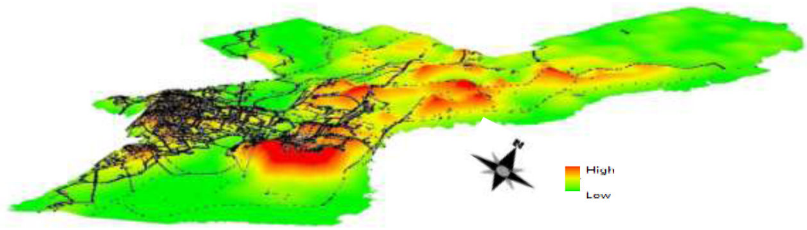


**Figure 3.**
Control participant daily paths overlaid on vandalism locations, 2007–2011

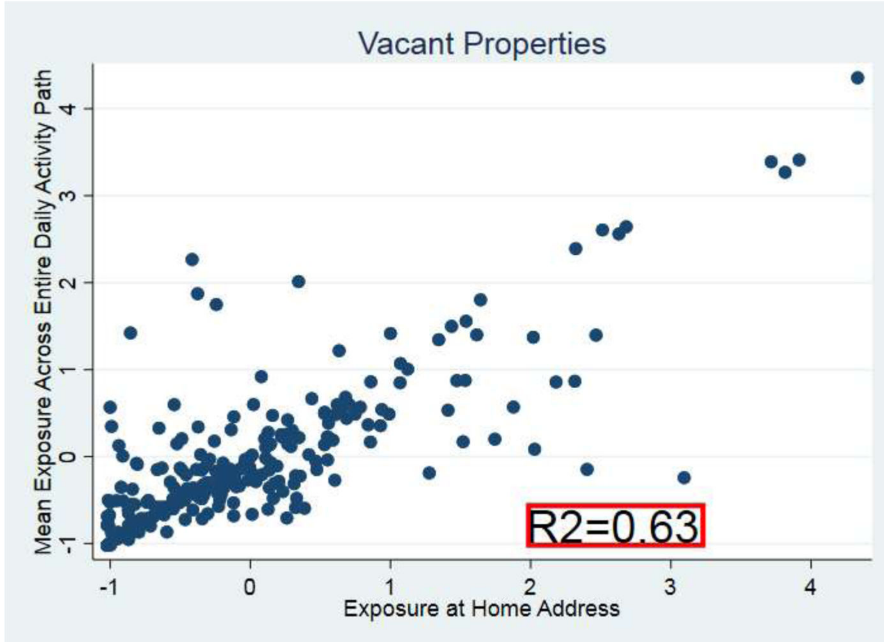


**Figure 4.**
Scatterplot comparing participants' exposure to vacant properties measured at home addresses versus mean exposure across entire daily travel paths

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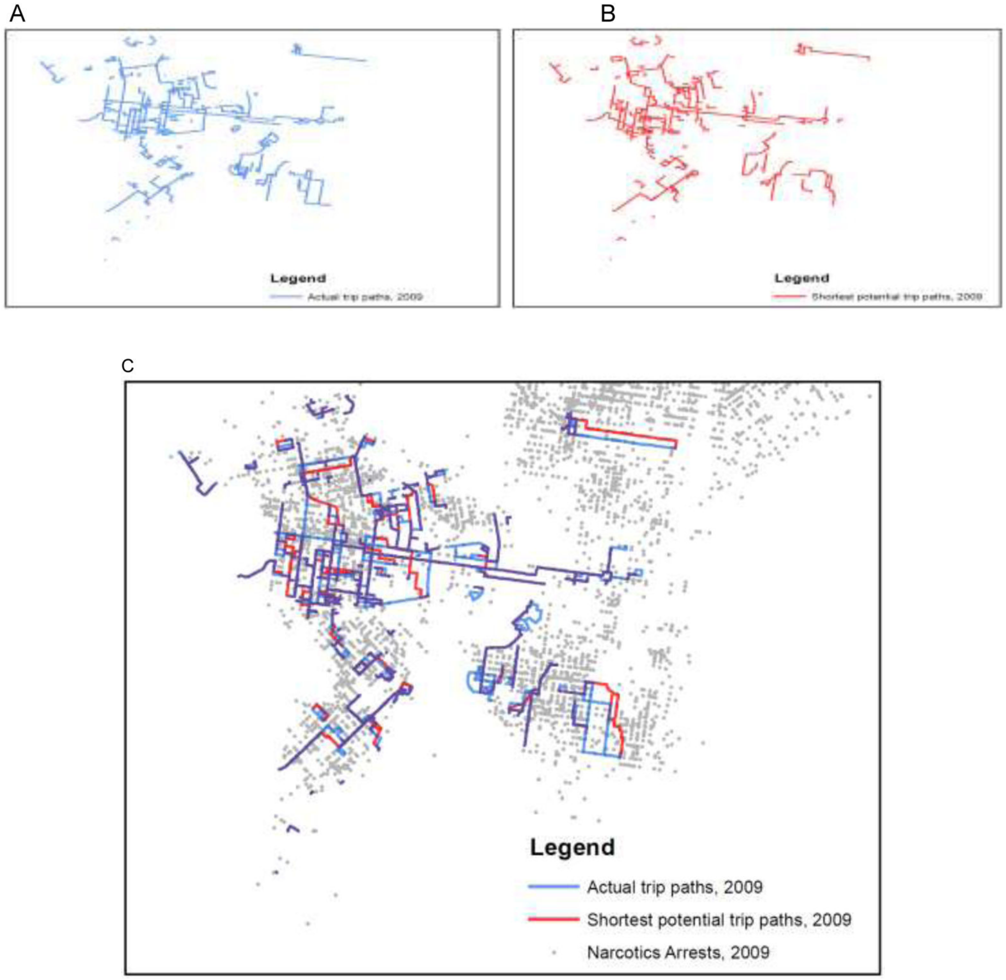


**Figure 5.**

Sample actual trip paths (A) and shortest potential trip paths (B), simultaneously overlaid on the location of narcotics arrests in Philadelphia (C), 2009

*dark blue lines represent areas of overlap between actual and shortest potential trip paths

**Table 1**

Characteristics of participants

| Characteristic | Control Participants (n=283) |
|---|---|
| Age, years, median (IQR) | 18.6 (15.8–20.8) |
| Race | |
| African American | 98.5% |
| Caucasian | 1.1% |
| Hispanic | 0.0% |
| Asian/Pacific Islander | 0.0% |
| Native American | 0.4% |
| Currently enrolled in school | |
| <18 years of age | 99.1% |
| ≥18 years of age | 44.3% |
| Receiving good grades in school (As/Bs) | 39.1% |
| Lifetime history of suspension or expulsion | 69.0% |
| Currently working | 35.8% |
| Participating in structured activities | 72.4% |
| Lifetime history of alcohol use | 65.3% |
| Lifetime history of marijuana use | 45.0% |
| Lifetime history of being jumped | 56.1% |
| Lifetime history of being in a fistfight | 91.9% |
| Lifetime history of going to hospital because of a fight | 12.8% |
| Lifetime history of carrying a weapon | 39.1% |
| Lifetime history of being on juvenile probation | 17.7% |
| Lifetime history of choosing travel route based on safety | 73.9% |
| Frequency of choosing travel route based on safety | |
| Monthly | 26.9% |
| Weekly | 19.8% |
| Daily | 17.9% |

## Table 2

Comparing environmental exposures measured at home addresses versus mean exposure across entire daily travel paths

| Environmental Exposure | Unit of measure | Raster Calculation | Home address-based measurement≠ Mean [SD] | Daily travel path- based measurement≠≠ Mean [SD] | p | $R^2$ |
|---|---|---|---|---|---|---|
| Median household income ($) | BG | IDW | 25963.68 [8614.6] | 26353.14 [7836.9] | 0.25 | 0.59 |
| Per capita income ($) | BG | IDW | 12584.99 [4657.8] | 13351.62 [4929.1] | 0.001 | 0.46 |
| Per capita unemployed (#unemployed per 1,000 residents age 16+) | BG | IDW | 82.5 [48.4] | 85.7 [44.0] | 0.19 | 0.37 |
| Per capita with at least some college education (# higher ed per 1,000 residents) | BG | IDW | 212.6 [106.9] | 236.7 [107.2] | <0.001 | 0.54 |
| Per capita black (# blacks per 1,000 residents) | BG | IDW | 827.2 [241.8] | 745.6 [253.0] | <0.001 | 0.51 |
| Per capita Hispanic (#Hispanics per 1,000 residents) | BG | IDW | 23.5 [51.2] | 26.3 [32.7] | 0.09 | 0.78 |
| Total population | BG | IDW | 811.2 [270.6] | 806.3 [238.4] | 0.67 | 0.51 |
| Population aged 15–24 | BG | IDW | 130.7 [48.7] | 128.4 [46.7] | 0.28 | 0.51 |
| Truancy rate | BG | IDW | 3.8 [2.4] | 3.7 [2.1] | 0.75 | 0.51 |
| Vandalism | Point | KD | 298.8 [122.8] | 288.7 [112.5] | 0.04 | 0.59 |
| Narcotics arrests | Point | KD | 315.1 [204.3] | 282.8 [164.8] | <0.001 | 0.65 |
| Disorderly conduct | Point | KD | 72.4 [45.1] | 81.7 [47.4] | <0.001 | 0.26 |
| Public drunkenness | Point | KD | 4.1 [15.4] | 6.3 [12.8] | 0.01 | 0.23 |
| Alcohol outlets | Point | KD | 14.4 [9.7] | 16.0 [11.3] | 0.003 | 0.39 |
| Alcohol expenditures by households ($) | BG | IDW | 326.9 [64.3] | 329.4 [62.5] | 0.35 | 0.57 |
| Vacant properties | Point | KD | 628.2 [593.5] | 602.7 [520.2] | 0.25 | 0.63 |
| Philadelphia recreation department facilities | Point | KD | 2.0 [1.8] | 1.9 [1.5] | 0.15 | 0.48 |
| Fire stations | Point | KD | 0.62 [0.82] | 0.64 [0.63] | 0.53 | 0.54 |
| Police stations | Point | KD | 0.47 [0.79] | 0.53 [0.68] | 0.11 | 0.42 |
| Neighborhood belonging | CT | IDW | 0.83 [0.10] | 0.84 [0.09] | 0.06 | 0.79 |
| Neighborhood improvement | CT | IDW | 0.76 [0.12] | 0.76 [0.10] | 0.81 | 0.76 |
| Neighbors help each other | CT | IDW | 0.83 [0.10] | 0.84 [0.09] | 0.06 | 0.79 |
| Trust among neighbors | CT | IDW | 0.56 [0.11] | 0.58 [0.10] | <0.001 | 0.64 |
| Participation in neighborhood organizations | CT | IDW | 0.41 [0.07] | 0.42 [0.05] | 0.18 | 0.75 |
| Stress experienced in past year | CT | IDW | 0.34 [0.06] | 0.35 [0.05] | 0.97 | 0.71 |
| Violence victimization in past year | CT | IDW | 0.02 [0.01] | 0.02 [0.005] | 0.003 | 0.64 |
| Firearms in or around home | CT | IDW | 0.06 [0.02] | 0.06 [0.02] | 0.02 | 0.72 |

[ǂ]Exposure calculated using raster layer value of the environmental feature at the participants' home address location

[ǂǂ]Exposure calculated by summing the raster layer values of the environmental feature at each 1-minute travel path point and dividing by the number of path points along the entire daily travel path

p = p value from t test comparing home address and daily travel path-based measurements

$R^2$ = R squared value from crude regression comparing home address (independent variable) and daily travel path-based (dependent variable) measurements

BG = Census block group CT = Census tract KD=Kernel density IDW=Inverse distance weighting

## Table 3

Measuring environmental exposure based on differences between actual trip paths and shortest potential trip paths, using point-level environmental exposure data

| Environmental Exposure | Difference in Cumulative Exposure, 60ft buffer β [95% CI] p value | Difference in Cumulative Exposure, 660ft buffer β [95% CI] p value | Difference in Exposure Density, 60ft buffer β [95% CI] p value | Difference in Exposure Density, 660ft buffer β [95% CI] p value |
|---|---|---|---|---|
| Vandalism | −1.76 [−2.53, −1.01] | −6.02 [−8.62, −3.43] | .806 [0.46, 1.15] | 357.23 [−52.13, 766.59] |
| | **P<0.001** | **P<0.001** | **P<0.001** | P=0.09 |
| Narcotics arrests | −1.96 [−2.80, −1.12] | −5.05 [−7.16, −2.93] | 2.31 [−0.35, 4.97] | 183.04 [52.53, 313.55] |
| | **P<0.001** | **P<0.001** | P=0.09 | **P=0.01** |
| Disorderly conduct | −1.29 [−2.23, −0.34] | −2.05 [−3.15, −0.94] | 0.74 [0.15, 1.33] | 80.41 [8.33, 152.48] |
| | **P=0.01** | **P<0.001** | **P=0.01** | **P=0.03** |
| Public drunkenness | −0.13 [−0.26, −0.004] | −0.24 [−0.47, −0.005] | 0.09 − [−0.02, 0.20] | 0.51 [−0.10, 1.12] |
| | **P=0.04** | **P=0.046** | P=0.13 | P=0.10 |
| Vacant properties | −0.19 [−0.50, 0.12] | −11.44 [−17.31, −5.57] | 0.92 [−0.10, 1.94] | 549.86 [−34.39, 1134.11] |
| | P=0.23 | **P<0.001** | P=0.08 | P=0.07 |
| Recreation centers | −0.007 [−0.02, 0.003] | −0.04 [−0.07, −0.01] | 0.0007 [−0.001, 0.003] | 1.41 [−1.07, 3.89] |
| | P=0.17 | **P=0.004** | P=0.50 | P=0.26 |
| Murals | −0.29 [−0.41, −0.17] | −0.72 [−1.12, −0.31] | 0.04 [−0.02, 0.11] | 56.72 [−26.19, 139.64] |
| | **P<0.001** | **P=0.001** | P=0.20 | P=0.18 |

## Table 4

Measuring environmental exposure based on differences between actual trip paths and shortest potential trip paths, using polygon-level environmental exposure data

| Environmental Exposure | Difference in Mean Exposure ‡ β [95% CI] p value |
|---|---|
| Per capita income ($)‡‡ | −17.21 [−271.90, 237.48] P=0.90 |
| Per capita unemployed ‡‡ | −1.21 [−3.99, 1.57] P=0.39 |
| Per capita with at least some college education ‡‡ | −0.85 [−4.32, 2.61] P=0.63 |
| Per capita black ‡‡ | −0.04 [−6.79, 6.72] P=0.99 |
| Per capita Hispanic ‡‡ | 0.21 [−0.54, 0.95] P=0.59 |
| Total population | −2.46 [−12.94, 8.03] P=0.64 |
| Population aged 15–24 | −0.47 [−2.56, 1.62] P=0.66 |
| Neighborhood belonging | 0.0003 [−0.001, 0.001] P=0.56 |
| Neighborhood improvement | −0.0005 [−0.002, 0.001] P=0.54 |
| Neighbors help each other | −0.0004[−0.001, 0.001] P=0.46 |
| Trust among neighbors | 0.0001[−0.002, 0.002] P=0.92 |
| Participation in neighborhood organizations | 0.0004 [−0.0004, 0.001] P=0.34 |
| Stress experienced in past year | 0.001 [−0.001, 0.002] P=0.53 |
| Violence victimization in past year | 0.00009 [−0.0001, 0.0001] P=0.82 |
| Firearms in or around home | −0.0001 [−0.001, 0.0003] P=0.53 |

‡Differences in mean exposures are calculated as follows: Diff (mean) = Weighted mean exposure encountered across polygons traversed along short route – weighted mean exposure encountered across polygons traversed along actual route

Subject level-mean values take the mean of these exposure differences across the unique trips = (diff1 + diff2 + diff3 + diff4...)/#trips

‡‡Per capita calculations reported per 1,000 residents; per capita unemployment calculated per 1,000 residents age 16 and older