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Community Greening, Fear of Crime, and Mental Health Outcomes

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Abstract

Unmaintained vacant land in urban areas is associated with a number of negative outcomes for residents of urban areas, including mental and physical health, safety, and quality of life. Community programs which promote land parcel maintenance in urban neighborhoods have been found to reverse some of the effects that unmaintained land has on nearby residents. We explored how land parcel maintenance is associated with mental health outcomes using data collected in Flint, MI in 2017–2018. Trained observers assessed the maintenance of approximately 7200 land parcels and surveyed 691 residents (57% Female, 53% Black, *M* age = 51). We aggregated resident and parcel rating data to 463 street segments and compared three structural equation models (SEM) to estimate the mediating effects of fear of crime on the association of parcel qualities on mental distress for residents. We found that fear of crime mediated the association between parcel maintenance values and mental distress indicating that poor maintenance predicted more fear of crime which was associated with mental distress. Our findings add to our understanding about the mechanism by which vacant lot improvements may operate to enhance psychological well-being of residents who live on streets with vacant and unkept lots.

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Conflict of Interest
The authors declare that they have no conflicts of interest. All research detailed in this article was done in compliance with APA ethical principles in its treatment of individuals participating in the research. The University of Michigan Institutional Review Board reviewed and approved as aspects of the research detailed in this article.

Keywords

Community greening; Fear of crime; Mental health; Urban health; Vacancy

Introduction

Population shifts have resulted in significant vacant land and deteriorating structures located disproportionately in low-income and minority urban neighborhoods (GAO, 2011; Heinze et al., 2018). Urban vacancy and physical disorder are associated with negative health outcomes for neighborhood residents (Mahoney et al., 2005), including greater crime incidence (Culyba et al., 2016), greater fear of crime (Branas et al., 2018; Kuo et al., 1998; Nasar, Fisher, & Grannis, 1993; Nasar & Jones, 1997), and more negative mental and physical health outcomes (Garvin et al., 2013a; Kuo & Sullivan, 2001). Residents with overgrown, untended lots nearby their homes have been found to have higher levels of depression, anxiety, and stress (Garvin et al., 2013b; Kuo & Sullivan, 2001). Unmaintained areas have potential to directly threaten the safety of neighborhood residents: Violent crimes are more likely to occur near unmaintained, vacant lots than maintained lots (Culyba et al., 2016), providing sites for illegal dumping (Garvin et al., 2013b) hiding spots for criminals and shelter for illicit activities (Branas et al., 2011; Donovan & Prestemon, 2012; Garvin et al., 2013b), and aggression in young males (Bohnert et al., 2009). The social health of neighborhoods is also significantly impacted by vacant land, through lower neighborhood satisfaction and increased perceptions of social disorder (Bohnert et al., 2010; Gardner, Browning, & Brooks-Gunn, 2012) which can fracture ties between neighborhoods (Garvin et al. 2013b). Indicators of physical disorder also impact perceptions of neighborhood investment, which may signal a weak sense of community in the neighborhood (Aiyer et al., 2015; Fredricks & Simpkins, 2012; Zimmerman et al., 2011).

Fear of crime is also a significant health consequence of vacant land (Branas et al., 2018; Nassar, Fisher, & Grannis, 1993). Indicators of urban disorder such as trash, debris, broken windows, unkempt lots, and overgrown shrubs or trees are associated with higher levels of crime and fear of crime for residents (Branas et al., 2018; Kuo et al., 1998; Nasar, Fisher, & Grannis, 1993; Nasar & Jones, 1997). According to a systematic review (Sreetheran & van den Bosch, 2014), indicators of the urban environment can provoke fear of crime victimization, relating to poor lighting, poor landscaping and dense vegetation, physical disorder, and incivilities. Researchers have reported that fear of crime can have negative consequences for health and well-being, by reducing mobility and physical activity, causing individuals to stay home (Gardner & Madriz, 1998; Hollander, 2001; Toby et al., 1982). Fear of crime has also been associated with more chronic health problems at the end of the 10-year study (Robinette et al., 2016).

Fear of crime can deter residents from walking in their neighborhoods, creating a cycle of avoidance, which researchers suggest perpetuates the continued decline of vacant, unkept land in the area (Foster et al., 2014). Community-organized interventions to address vacancy and deterioration can provide the resources necessary for neighborhoods to address abandoned properties, not only to beautify their neighborhoods but to improve the health, well-being, and safety of residents (Jennings & Gaither, 2015). One form of intervention that cities are undertaking to remediate vacancies in urban environments is through community greening and associated maintenance activities (Heinze et al., 2018; Krusky et al., 2015; Reischl et al., 2016). Greening projects promote controlled growth and maintenance of natural areas, such as parks, gardens, and residential lawns. A greened property parcel has evidence of maintenance including groomed grass, bushes, trees or other natural landscaping, or planted areas such as a rock, flower, or vegetable garden (Reischl et al., 2016). Carter et al., (2003) found that engaging community members to address a problematic land corridor was successful at reducing crime reports against persons and property, prostitution, and narcotics over an eight-year span (Zimmerman et al., 2011). Access to natural areas such as small parks and gardens may also improve mental health, reduce crime, and promote good health and well-being (Bartuska, 2013; Gardner, Roth, & Brooks-Gunn, 2008; U.S. Department of Health and Human Services, 2008).

Addressing physical indicators of disorder through greening has been successful in a number of cases at reducing fear of crime (Branas et al., 2018; Garvin et al., 2013a). In a citywide cluster randomized controlled trial of greening interventions, Branas et al., (2018) restored vacant land over three years to test the effects of vacant land restoration on violence, crime, fear, and perceptions of safety. The researchers attributed a 58% reduction in resident's safety concerns and a 76% increase in the use of outside spaces to the greening interventions. In their review, Sreetheran and van den Bosch (2014) also concluded that open views, maintained grass and vegetation, and visible escape paths, have been associated with more feelings of safety. Other researchers have also found that increased perceptions of safety have been found to be associated with improved health, for example lower blood pressure (Mayne et al., 2018).

While prior studies have found generally positive direct impacts of parcel improvements separately on crime and health, the mechanisms behind and relationships between these associations are under-explored. It has not been tested whether parcel improvements improve mental health via reduced fear of crime. To test this hypothesis, we estimated the relationship between parcel maintenance levels as measured during citywide greening interventions, fear of crime, and mental health of residents in Flint, Michigan.

Methods

The data used for this study were collected by researchers at the Michigan Youth Violence Prevention Center (MI-YVPC) as a part of their involvement in community greening programs in Flint, Michigan. During the summer months (May-September) of 2017–2018, trained research assistants collected data from neighborhoods where community greening activities were ongoing. Research assistants recorded observations of land parcels and administered surveys to residents living on specific street segments.

Flint, MI has experienced drastic impacts from deindustrialization. Namely, population decline since the 1962 has resulted from relocation of the auto industry, and then a crisis of lead found in drinking water starting in 2014. As a result, Flint has high rates of vacancy and high rates of poverty and crime. The Genesee County Land Bank (GCLB) operates a large-scale effort to maintain the vacant land in the city, and served as our community partner. The GCLB community greening program focused primarily on vacant lot remediation, which may have included lot clean up, mowing, planting grass, and/or maintaining a community garden. The community greening activities were not standardized across the parcels, but were instead directed by community groups and influenced by the needs of the specific neighborhoods. Our unit of analysis was the street segment, defined as block faces from one corner to the next and both sides of the street. Researchers were assigned to collect data from street segments if the street segment had at least one parcel being maintained by GLCB's community greening program. We obtained data on the location of street segments from the Michigan GIS open data portal (State of Michigan GIS Open Data, 2015).

We also collected data on street segments with vacant lots that were not remediated in any way. We selected these other street segments based on proximity to the remediated lots; street segments with lots that were not remediated were included if the center of the lot was within 200 meters of the center of a remediated lot, which is consistent with prior research using this method of street segment assessment (Reischl et al., 2016). A total of 7239 parcels were assessed, and 691 residents were surveyed during these years (see Figures 1 and 2 for locations of parcels and survey data collection). The University of Michigan Institutional Review Board approved all aspects of this research.

Procedures

A team of trained observers conducted parcel assessments by visiting each land parcel on street segments in the parent study. All parcels included in MI-YVPC programs were assessed three times during the summer months: pre-greening, post-greening, and during a one-year follow-up. We used only post-greening data in the current analyses. While some parcels may have been assessed in multiple years or waves, none of the parcels that were included in the current sample were assessed in both 2017 and 2018 and each parcel appears only once in the dataset.

During parcel assessments, research assistants also recruited a sample of neighborhood residents by going door-to-door on each street segment. Researchers knocked on all household doors on a street segment, and a randomly selected adult in the household completed the Neighborhood Life Survey (NLS; described below). Prior to having participants complete the questionnaire, the researchers obtained consent for participation from each resident. Participants completed the study voluntarily and were not provided with compensation for their participation. The researchers assisted each respondent in answering survey questions and entered their responses directly into Qualtrics. Surveys were administered on each street segment during each of the three rounds of parcel assessment. We use the NLS data from the second, post-greening round of data collection which occurred during the summer months of 2017 and 2018.

Sample

The current study uses a sample of the data collected during YVPC's larger data collection efforts and partnership with the GCLB, during which parcel observation data were collected from approximately 4200 street segments from 2017 to 2018. For the purposes of the current study, all of the data used in the following analyses, including individual, parcel, and census data, were aggregated to the street segment level. We included an individual's data at the aggregated level if it had been matched to a specific street segment and had completed our primary individual measures, mental health, and fear of crime, in full. Street segments were excluded from analysis in this study if researchers did not collect survey data from residents on the street segment. Additionally, if researchers conducted a parcel assessment, but were unable to collect individual fear of crime or mental health data from any neighborhood residents, that street segment was excluded from the current study. Of the 4200 street segments which parcel assessments had been conducted, our final sample includes 463 street segments with both aggregated parcel assessment values and resident survey responses (approximately 10% of all street segments). Within this sample of street segments, 203 street segments had ongoing community greening activities, and 260 did not.

The mean number of parcels per street segment was 15.63 (*SD:* 9.17), with a minimum of one parcel and a maximum of 43 parcels per street segment. We used data from 691 individual NLS respondents to create the models described below (see Table 1 for all descriptive statistics). The mean number of respondents per street segment was 1.77, with a minimum of one respondent and a maximum of 14 respondents matched to a street segment. The mean age of included NLS respondents was 51.1 years, with a minimum age of 18 years and a maximum age of 90 years. Fifty-seven percent of the sample identified as female, 53% of the sample identified as Black, and 37% of the sample identified as White.

Measures

Parcel Maintenance—We used the Parcel Maintenance Observation Tool (PMOT; Reischl et al., 2016) for assessing the quality of parcels on a street segment. PMOT is an observational tool that assesses the maintenance and upkeep of land parcels involved in community greening projects. Research assistants were trained to assess parcels in pairs, and when they reached 80% consensus on parcel assessment, were allowed to assess parcels as individuals. Research assistants used the PMOT to note the presence or absence of broken windows, graffiti, fire damage, among other indicators of physical disorder, as well as the upkeep of landscaping, mowing, and buildings on each parcel. The average inter-rater correlation for PMOT coders ranged from 0.79 to 0.93.

We calculated a *General Parcel Maintenance* value for each parcel that was assessed using the PMOT. The General Parcel Maintenance Scale (GPMS) *is* a subscale of the PMOT which considers the presence or absence of building deterioration (e.g., broken windows, boarded doors, graffiti), landscaping, and litter in the assessed parcel of land. The GPMS is calculated by standardizing and recoding observations so that higher values indicated better parcel maintenance. After observers assessed parcels using the PMOT, we grouped parcels according to the closest street segment ArcGIS Pro (ERSI, 2020), and aggregated GPMS values for each parcel to create a mean general parcel maintenance value for each street segment. The mean value for the GPMS was 0.16 (*SD*: 0.31, Range: −0.97, 0.92). High values on the GPMS indicate that the physical structures of the parcel (windows, doors, and buildings) are not damaged, its landscaping is not overgrown and appears to be maintained, and the parcel is free of litter/trash. The sample of parcels we used in these analyses were rated slightly above average for general parcel maintenance; we z-scored each data point before street segments were matched to NLS data to calculate values for the GPMS.

Neighborhood Life Survey—The Neighborhood Life Survey is a self-reported instrument developed by the MI-YVPC that includes several psychosocial variables which assess psychological well-being, social capital, and neighborhood perceptions including attitudes about neighborhood crime and safety. We used measures of fear of crime, mental distress, and victimization from the NLS to test our hypotheses.

Fear of crime.: The fear of crime measure has 4-items with a Likert-type response scale, including: How fearful respondents are of crime in their neighborhood from 1 (*Not Fearful at All*) to 4 (*Very Fearful*); how respondents perceive the crime rate in their neighborhood compared to other neighborhoods from 1(*Very Low*) to 3 (*About the Same*) to 5 (*Very High*); how dangerous or safe it is to walk in the respondent's neighborhood during the daytime; and how dangerous or safe it is to walk in the respondent's neighborhood after dark 1(*Completely Safe*) to 4 (*Extremely Dangerous*; $\alpha = 0.85$). We generated a z-score and averaged individual responses to the four items to calculate an individual fear of crime value, with higher scores indicating greater fear of crime. We then aggregated individual scores to the street segment level to create a mean fear of crime value for each street segment. The mean value of fear of crime in our dataset was centered at 0.00 (*SD:* 0.75, Range: −1.62, 1.71).

Mental distress.: We measured mental distress using 6-items with a Likert-type scale from 1(*Never*) to 5 (*Very Often*), which asked respondents to report, in the past week: How often they felt upset because of something that happened to them; felt nervous or stressed out; felt like they could not deal with their problems; felt lonely; felt blue or sad; and felt no interest over the past week ($\alpha = 0.91$). We z-scored and averaged individual responses to calculate an individual value of mental distress, with higher scores indicating greater mental distress. We then aggregated individual scores to the street segment level to create a mean mental distress value for each street segment. The mean for mental distress was 2.08 (*SD*: 0.88, Range: 1.00, 5.00). The NLS respondents that we included in the present analyses reported average mental distress levels slightly below the midpoint of the scale.

Covariates—We included several individual level and neighborhood context covariates from various sources in our model testing to eliminate alternative explanations of the results. All of the covariates were also aggregated to the street segment level. We controlled for individual-level variables that could confound the association between parcel characteristics, mental health, and fear of crime such as prior victimization, demographic variables, and years of residence as reported in the NLS.

Victimization.: Prior victimization occurring on a resident's street segment could increase an individual's mental distress and fear of crime (Snedker, 2012). We calculated victimization using two items from the NLS. Respondents indicated "yes" or "no" if, in the past two years, they had been 1) in a physical fight resulting in injury and/or, 2) been the victim of a crime. Possible scores ranged from 0 to 2, with zero indicating having not been involved in either a physical fight or been the victim of a crime, one indicating either being in a physical fight OR being the victim of a crime, and two indicating having been involved in BOTH a physical fight and having been a victim of a crime. We averaged individual responses to these two items to create an individual value for victimization. We aggregated individual victimization values to the street segment level to create a mean value of victimization for each street segment. The mean value for victimization was 0.26 (*SD*: 0.44, Range: 0.00, 2.00). An average of 13% of respondents on each street segment reported either having been in a physical fight or being a victim of a crime in the two years prior to completing the NLS.

Years residing on the street segment.: Years of prior residence on a street segment could affect an individual's fear of crime occurring in the neighborhood (South et al., 2018). NLS respondents reported how many years they had been living at their current address. We aggregated individual responses to the street segment level to create an average number of years of residence for each street segment.

Demographic variables.: Demographic characteristics including race, sex, and age are also known to affect perceptions of safety (Kondo et al., 2018; Lorenc et al., 2012). Residents self-identified with one or multiple race and gender identities. We recoded responses into indicator variables for all possible responses, such that each resident's self-identification for race and gender could be represented by a set of "0"s and "1"s. We then created percentages by averaging responses at the street segment-level. The age variable was created by assigning a "0" to all residents younger than 65 and a "1" to all residents 65 and older. We then averaged by street segment to create a percentage of residents 65 and older on each street segment. The following percentages were included in the models: Percentage of White-identifying residents, percentage of female-identifying residents, and percentage of residents indicating that they were age 65 or older. All of these percentages were at the street segment level.

We also include several contextual variables as covariates in our analysis including police incidents for crime and census data for a neighborhood socioeconomic status measure.

Kernel Density Crime Incidence.: We calculated the density of Part I violent crime incidents which occurred during the summer months (May-September) in 2017–2018, using Michigan Incident Crime Reporting (MICR) data. MICR data are administrative data reported to the Michigan State Police by participating law enforcement agencies throughout the state (MSP, 2019). Part I crimes include violent crimes such as murder, sex offenses, and aggravated assault, and property crimes such as robbery, burglary, and motor vehicle theft. The Flint City Police Department is the primary reporting agency for these data. An incident refers to a reported event that a law enforcement official judges to be a crime regardless whether an arrest was made or not.

To estimate the density of crime incidents at each street segment, we calculated kernel density raster layers for 2017 and 2018 crime data using ArcGIS Pro (ESRI, 2020). For these calculations, we specified a 50 × 50 meter cell size and an 850 meter bandwidth. We used ArcGIS's default method for calculating an optimized bandwidth distance, which is based on a multi-dimensional adaptation of Silverman's rule-of-thumb (ESRI, n.d;

Silverman, 1986). We then extracted the crime density value from the kernel density raster layer at the centroid of each street segment. We report these density values in units of crimes per square mile.

Census data.: We also used Census data to calculate an additional set of control variables, including population density and an index of neighborhood disadvantage. We matched sociodemographic data to street segments by determining in which Census block group the largest portion of each street segment fell. For each street segment, we calculated a value for neighborhood disadvantage similar to that of Sampson et al., (1997) using the American Community Survey (ACS) data (2014–2018 estimates) using percent of households in poverty, on public assistance, renter-occupied units, and vacant properties. We created a mean disadvantage value for each street segment with greater values on this index indicating greater disadvantage at the street segment level.

Data Analytic Strategy

We tested three hypothesized models using structural equation modeling (SEM) in R/RStudio (R Core Team, 2020) using the "*lavaan*" package (Rosseel, 2012). We built all models with observed variables and calculated all standard errors using maximum likelihood (ML) estimation with 1000 bootstrapped samples. The assumption of independence required for ML estimation was met. First, we tested a simultaneous regression model (Model 1) to estimate the associations between the parcel maintenance, fear of crime, and all control variables, and mental distress. The purpose of this model was to determine whether general parcel maintenance and fear of crime are associated with mental health, and to estimate the main effects of general parcel maintenance and fear of crime on mental distress when controlling for the appropriate set of control variables. Second, we tested a fully saturated model (Model 2) to estimate the association between the parcel maintenance and mental distress that included all direct effects and the mediating effects of fear of crime and including all control variables in the model. Lastly, we tested a more parsimonious model (Model 3) which estimated the relationship between parcel maintenance, fear of crime, and mental distress without estimating the direct association between parcel maintenance and mental distress. We estimated the standardized beta coefficient for each model path and 95% confidence intervals for each coefficient.

We calculated fit statistics and diagnostics to determine which model best fit the data. We used multiple indices to determine model fit: proportion of variance explained (R-Square), model chi-square, Comparative Fit Index (CFI; Bentler, 1990), Tucker-Lewis index (TLI; Tucker & Lewis, 1973), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA), setting our criteria for good model fit at CFI/TLI > 0.90, SRMR < 0.08, and RMSEA < 0.06 (Hu & Bentler, 1999). We also assessed the statistical significance of each model pathway. We used a chi-square difference test to compare Models 2 and 3 to determine whether the more parsimonious model was a better fit to the data.

Results

Correlation Analyses

A bivariate correlation matrix of all included variables is presented in Table 2. General parcel maintenance was not correlated with fear of crime ($r = -0.18$, $p = 0.15$) or with mental distress ($r = -0.15$, $p = 0.23$). Street segments with higher mean levels of mental distress also have higher levels of fear of crime ($r = 0.41$, $p < 0.01$) and victimization ($r = 0.31$, $p < 0.05$). Fear of crime was not correlated with number of Part 1 crimes reported in the years prior ($r = 0.06$, $p > 0.05$).

Structural Equation Models

Our first model estimated the associations between mental distress and parcel maintenance, fear of crime, and all control variables (see Figure 3a). We found that when including all control variables, general parcel maintenance was not associated with mental distress (*b*: −0.101, 95% CI: −0.362, 0.157). We found that more fear of crime and was associated with more mental distress (*b*: −0.299, 95% CI: 0.216, 0.388).

Our second fully saturated model tested for mediation between general parcel maintenance, fear of crime, and mental distress with all control variables included (see Figure 3b). This model included both the direct effect of parcel maintenance on mental distress and the indirect effect through fear of crime. This model indicated that street segments with higher parcel maintenance scores had lower fear of crime (*b*: −0.371, 95% CI: −0.617, −0.120). Replicating the same relationship as in model 1, fear of crime was associated with mental distress (*b*: 0.375, 95% CI: 0.251, 0.475). We found no direct association between parcel maintenance on mental distress with all control variables included (95% CI: −0.445, 0.070). The standardized beta for the indirect association between parcel maintenance on mental distress through fear of crime was −0.139.

Our third model estimated the relationship between general parcel maintenance, fear of crime, and mental distress with all control variables included, but we did not estimate the direct association between general parcel maintenance and mental distress (see Figure 3c). Replicating the previous models, parcel maintenance was negatively associated with fear of crime (*b*: −0.358, 95% CI: −0.603, −0.085). Fear of crime was associated with mental distress (*b*: 0.388, 95% CI: 0.263, 0.492). We calculated the indirect association between general parcel maintenance and mental distress to be a standardized beta of −0.139. All path estimates for Models 2 and 3 are listed in Table 3, and a path diagram with significant estimates for Model 3 can be found in Figure 4. This third mediation-only model was a slight, but significant improvement from the fully saturated model (Model 2) based on the chi-square change test (χ^2 *dif.* = 2.223, $df = 1$, $p > 0.05$; see Table 4 for all fit statistics).

Discussion

Our results supported our hypothesis that the effects of parcel maintenance on mental distress are through its effects on fear of crime. That we did not find a direct effect of parcel maintenance on mental distress strengthens the interpretation that improving neighborhood property conditions has an indirect effect on the psychological well-being of the residents living there. Our finding that fear of crime is associated with mental distress also suggests that crime prevention efforts may both reduce crime and improve the mental health of the residents where the crime occurs. Our findings build upon prior research confirming that fear of crime is related to more negative health outcomes for neighborhoods (Branas et al., 2018; Kuo et al., 1998; Nasar, Fisher, & Grannis, 1993; Nasar & Jones, 1997) and builds on it by identifying how greening or vacant lot maintenance may operate to improve the well-being of those living in high vacancy areas.

Our findings are further strengthened by the fact that we controlled for several potential spurious variables. Victimization does not account for our results even though it is often found to be the primary source of fear of crime, especially for women (Snedker, 2012). While our findings contribute to the notion that neighborhood environmental conditions impact one's fear of risk of victimization, these conditions likely have an indirect effect on mental distress through other means as well. Similarly, the density of crime occurrence on a particular street does not account for mental distress at the street segment level. Finding that parcel maintenance is associated with less mental distress through reduced fear of crime suggests that improved environmental conditions alone may have a positive effect on psychological well-being regardless of crime rate. Future interventions focused on improving community mental health may benefit from a multi-faceted approach which addresses physical characteristics of the neighborhood in addition to other factors which directly impact crime occurrence at the street segment level.

Similarly, neighborhood disadvantage does not account for variability in our measures of fear of crime or mental distress. Our measure of disadvantage included economic indicators of poverty and vacancy; thus, neighborhood economic disadvantage did not eliminate the relationships between parcel maintenance, fear of crime, and mental distress. This is especially vital given that these measures assess contextual variables but are still associated with individual-level experiences. However, the finding that neighborhood disadvantage is unrelated to our outcome measures may be limited to the current study due to low variability on these disadvantage measures. Many, if not all of the greening activities detailed in this study were conducted in neighborhoods with a high disadvantage index, which limits the variability of this measure and its ability to account for variations in neighborhood-level mental health or fear of crime.

We found it especially noteworthy that parcel maintenance is not directly related to mental distress. This may indicate that land management interventions which emphasize crime prevention serve to reduce residents' fear of crime, utilizing the mechanism by which physical characteristics of a neighborhood contribute to mental health. Sreetheran and van den Bosch (2014) suggest that vacant land mitigation may help reduce residents' fear of crime by creating more open views and visible escape routes (Sreetheran & van den Bosch, 2014). Community greening programs may also send a message to potential criminals that the place is being cared for by the community (Jiang et al., 2018; Yang et al., 2013), given that some of these programs have been effective at decreasing crime in the surrounding areas (Garvin et al., 2013b; Branas et al., 2016). However, while not a primary finding of this study, we did not find a significant relationship between a street segment's crime density and the fear of crime its residents reported (see Table 2 for bivariate correlations).

Given our finding that fear of crime is a primary influence on the mental health of urban neighborhoods, future research should examine the complicated relationships between vacant lot remediation and management, its impacts on neighborhood crime, and residents' fear of crime as a gateway through which other mental and physical health outcomes pass through.

Several study limitations should be noted. First, our analyses did not account for change over time. Our individual- and parcel-level data were collected at a timepoint after the land parcels had been greened and were being maintained, and using two years of data resulted in street segment-level variability in parcel maintenance values which allowed us to make more robust conclusions. Nevertheless, we are not able to make any causal claims about the land parcel maintenance' s direct influence on the fear of crime or mental health of neighborhoods.

Second, our data are all aggregated at the street segment level, making it impossible to assign respondent demographics to specific survey responses. Nor could we could not stratify our analyses by individual-level characteristics (e.g., gender, age). Others have found that fear of crime differs between men and women (Lane & Fisher, 2009; Snedker, 2012, 2015); accounting for individual-level demographics instead of aggregate, percentage-based demographics may yield different results between say, men and women.

Additionally, our method of aggregation to the street segment level allows us to make conclusions on a large, neighborhood-level scale; however, this also assumes that the individual respondents on each street segment were representative of all residents on a street segment. One could also argue that multilevel modeling would yield a more accurate estimation of the relationships analyzed here. However, the structure of our dataset limited our ability to estimate multilevel models; our respondent-level data were not matched in any way to parcel-level data, which would not allow for an informative "Level 1" equation in a multilevel structure. This required us to aggregate up to the street segment in order to match our variables at the same unit of measurement. Although this may reduce our generalizability to some extent, the fact that we found effects across 463 street segments suggests that sampling bias or methods of aggregation are unlikely explanation for our results.

Finally, while the Genessee County Land Bank is involved in parcel maintenance activities across the city of Flint, we cannot be certain that other greening programs were not ongoing during YVPC data collection. If other greening programs were going on, this could have skewed our "control" street segments toward having greater parcel maintenance values and limited the variation we find in parcel maintenance. In other words, the size of the relationships detailed in this study may be larger than we found in this sample, due to potential contamination by parcel maintenance outside of the GCLB activities. Future studies should take steps to control for this potential.

Conclusions

Our study is one of the first to examine fear of crime as the primary mechanism by which the physical characteristics of a neighborhood impact the mental health and distress of residents. Our results provide evidence that community greening programs, especially those which target vacant, unkept lots, are an effective approach for improving mental health in economically disadvantaged neighborhoods across the rust belt of the United States.

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High Lights

- Land parcel greening is associated with positive outcomes for urban neighborhoods.
- Neighborhoods with greater parcel maintenance also had less fear of crime and less mental distress.
- Community greening may improve mental health outcomes through decreasing fear of crime.

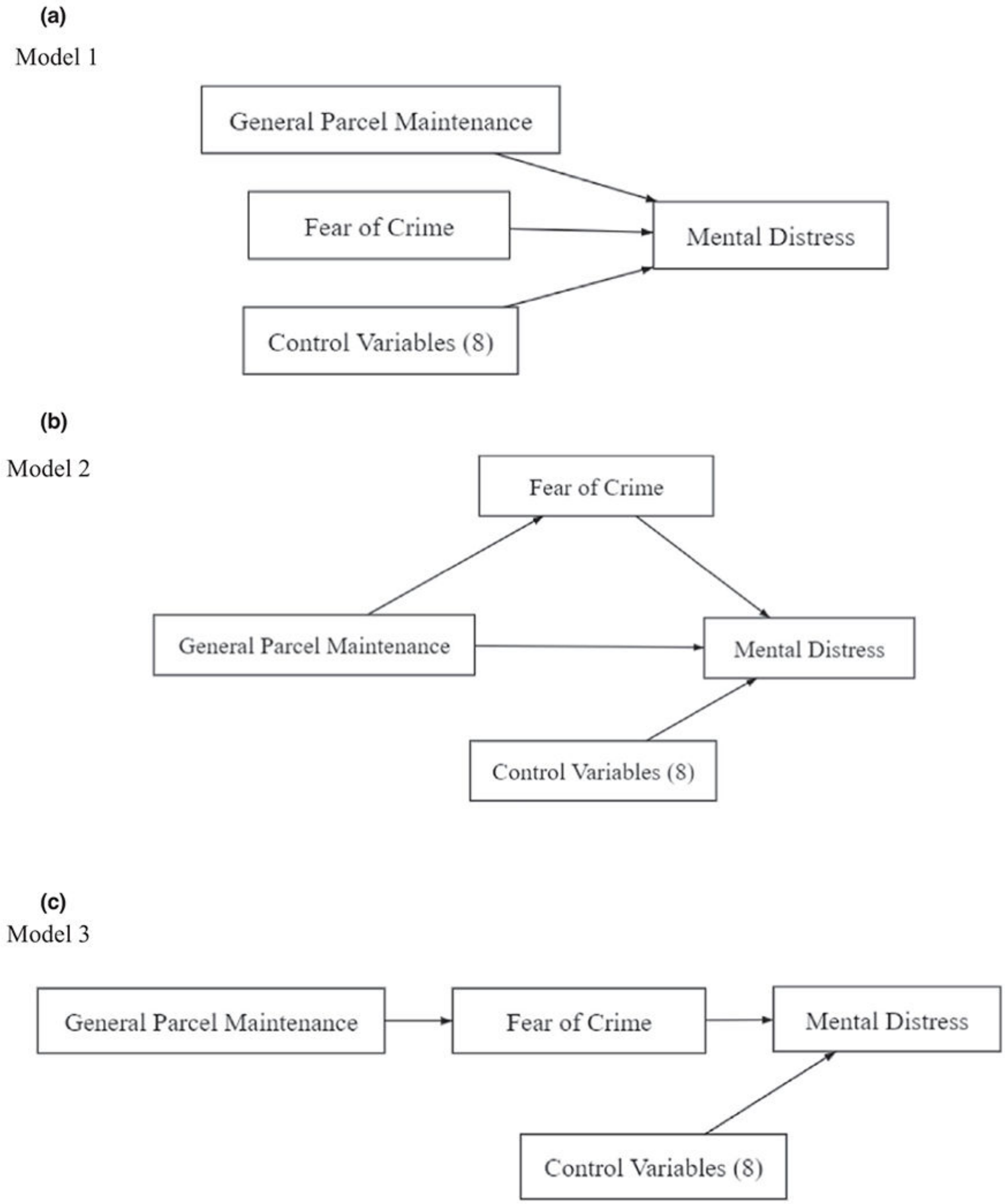

Figure 1.
(a, b) Map of Parcels assessed using PMOT in Flint, MI (2017 & 2018).

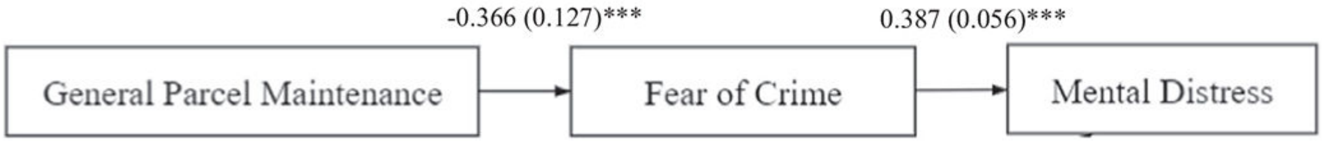

Figure 2.
(a,b) Map of Street Segments where NLS was administered to residents (2017 & 2018).

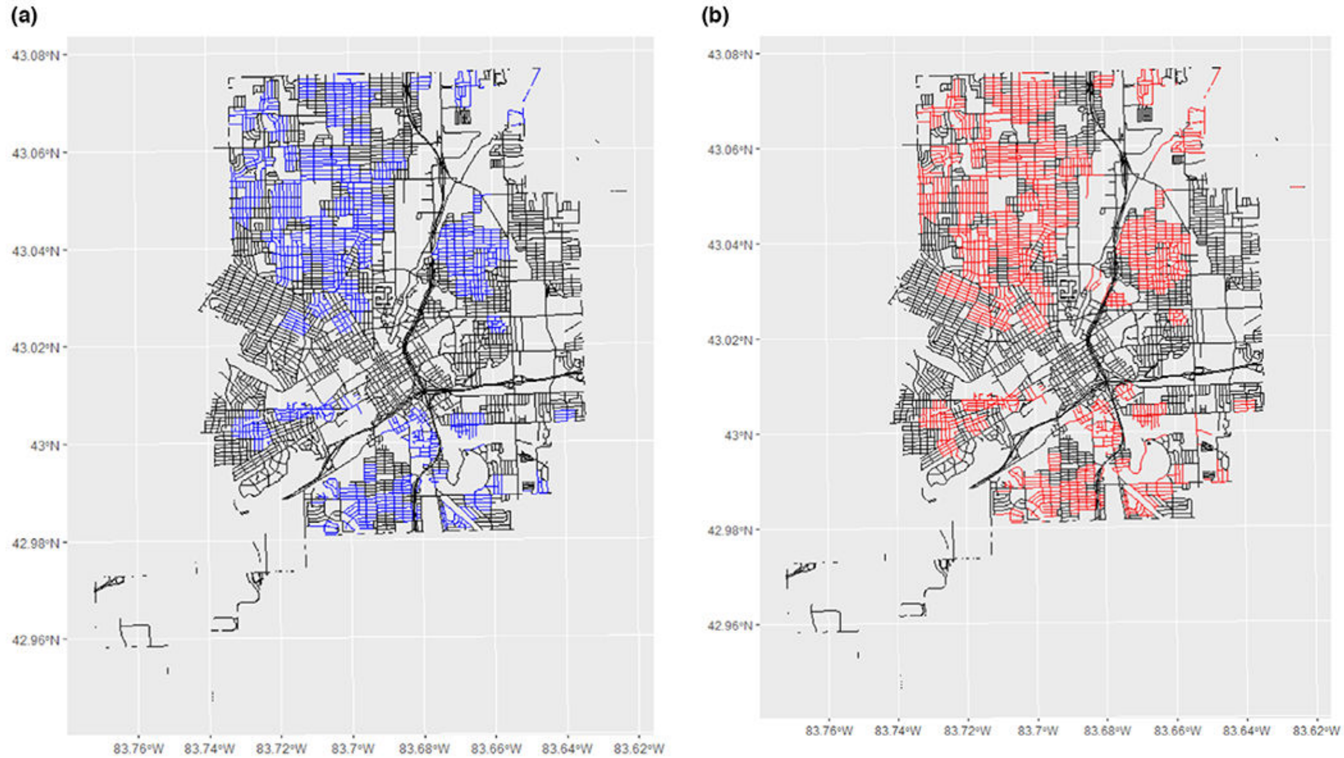

Figure 3.
(a, b, c) Theoretical SEM Path Diagrams.

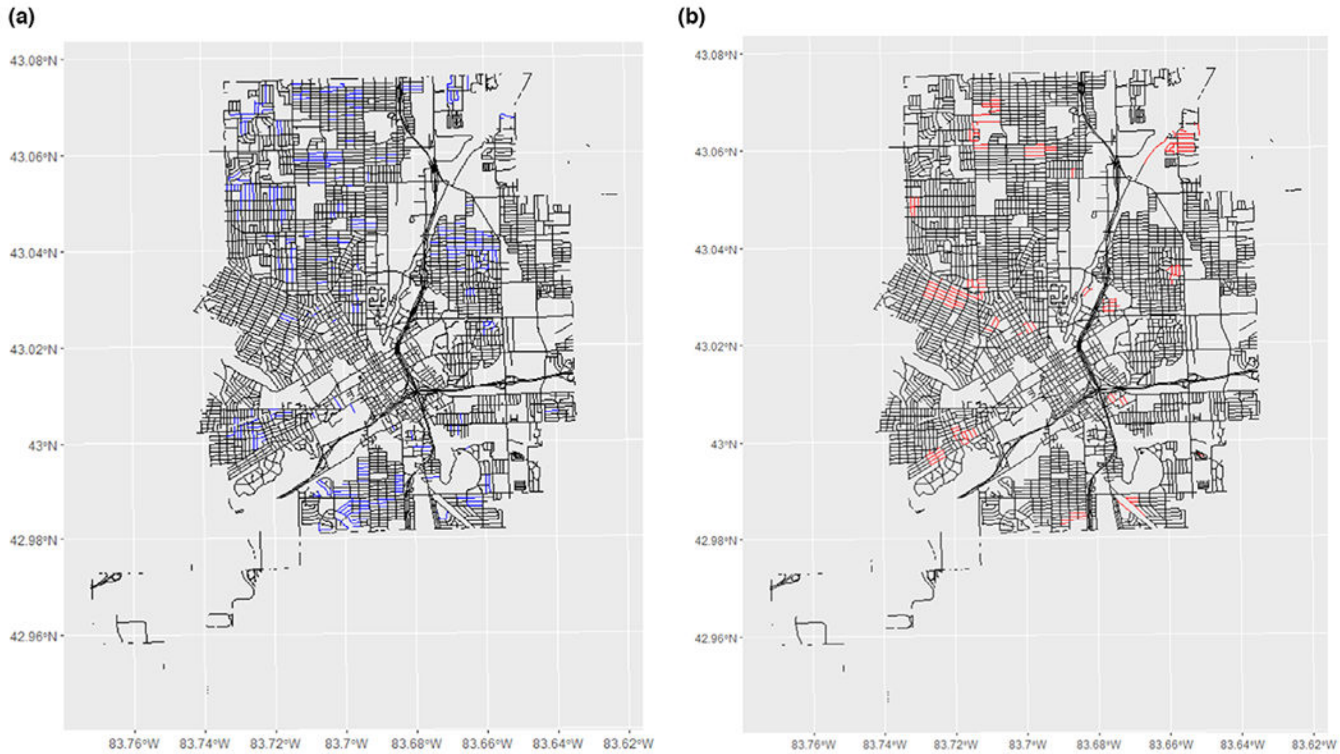

Figure 4.

Standardized Beta parameter estimates for final SEM path model with all covariates included.

Table 1

Descriptive statistics on all predictor variables, outcome variables, mediator variables, covariates, and dataset descriptors

Type	Data source	Variable	Mean (SD)	Range	Skew
Predictor	PMOT	General Parcel Maintenance Scale	0.16 (0.30)	−0.81–0.92	−0.42
Mediator / Predictor	NLS	Fear of crime	0.00 (0.73)	−1.63–1.69	0.14
Outcome	NLS	Mental distress	2.06 (0.87)	1.00–5.00	0.80
Covariate	NLS	Age	51.12 (15.26)	18–96	0.00
Covariate	NLS	% female	0.57 (0.43)	0.00–1.00	−0.28
Covariate	NLS	% White	0.37 (0.45)	0.00–1.00	0.52
Covariate	Census	Disadvantage Index - New	0.30 (0.09)	0.11–0.50	0.15
Covariate	NLS	% Age 65 or older	0.25 (0.38)	0.00–1.00	1.21
Covariate	NLS	Victimized in last two years	0.26 (0.44)	0.00–2.00	1.65
Covariate	NLS	Years of residence	16.55 (14.77)	0.08–70.00	1.01
Covariate	Census	Population Density	0.002 (0.001)	0.0003–0.004	0.63
Covariate	Crime Density	2015–2017, Summer	28.64 (21.47)	0.13–198.11	2.32
Descriptive	PMOT	# Parcels per Street Segment	15.63 (9.17)	1–43	0.39
Descriptive	NLS	# Respondents per Street Segment	1.77 (1.26)	1–14	3.65
Descriptive	NLS	% Black	0.53 (0.47)	0.00–1.00	−0.11
Descriptive	Census	Disadvantage Index - Sampson & Raudenbush	0.32 (0.08)	0.14–0.51	−0.08
Descriptive	Crime Density	2015–2017, Full Year	62.53 (38.51)	4.62–367.71	2.41

Table 2

Bivariate correlation matrix of all variables included in SEM models

	1	2	3	4	5	6	7	8	9	10	11
1, Parcel maintenance	1.00										
2. Fear of crime	−0.18	1.00									
3. Mental distress	−0.15	0.41***	1.00								
4. Victimization	−0.08	0.20	0.31*	1.00							
5. Disadvantage index - New	−0.20*	0.13	0.07	0.08	1.00						
6. Population density	0.29*	−0.01	0.01	0.03	−0.22*	1.00					
7. Years residing	−0.02	−0.02	−0.17*	−0.12	0.05	−0.15	1.00				
8. Age	0.08	−0.11	−0.28**	−0.16*	0.02	−0.04	0.51***	1.00			
9. % White	0.09	0.23	0.17	0.24*	−0.03	0.09	−0.14	−0.07	1.00		
10. % Female	0.09	0.07	0.01	−0.10	−0.02	0.08	−0.01	0.16	0.02	1.00	
11. % > 65	0.11	−0.10	−0.24**	−0.17*	−0.01	0.02	0.40***	0.72***	−0.11	0.13	1.00
12. Crime density - Summer	−0.11	0.07	0.01	0.01	0.19	0.25	0.01	−0.05	−0.11	−0.02	−0.02

* $p < 0.05$;

** $p < 0.01$;

*** $p < 0.001$.

Table 3

Model coefficients - models 2 (Mediation) and 3 (Path)

Outcome variables	Predictor variables	Standardized coefficients (SE) Model 2 - mediation	Standardized coefficients (SE) Model 3 - Path model	CIs (95%) Model 2 - mediation	CIs (95%) Model 3 - Path model
Fear of crime	Parcel maintenance	−0.371 (0.126) **	−0.358 (0.130) **	[−0.617, −0.120]	[−0.603, −0.085]
	Victimization	0.135 (0.029) ***	0.136 (0.027) ***	[0.078, 0.192]	[0.081, 0.187]
	Disadvantage index	0.027 (0.028)	0.029 (0.027)	[−0.025, 0.084]	[−0.023, 0.082]
	Population density	−0.029 (0.025)	−0.037 (0.025)	[−0.078, 0.021]	[−0.086, 0.010]
	Years residing	−0.018 (0.029)	−0.018 (0.028)	[−0.073, 0.037]	[−0.072, 0.038]
	% White	0.224 (0.064) ***	0.218 (0.066) ***	[0.098, 0.348]	[0.100, 0.357]
	% Female	0.125 (0.063)	0.122 (0.061) *	[−0.004, 0.241]	[0.001, 0.244]
	% >65	−0.214 (0.074) **	−0.221 (0.070) **	[−0.361, −0.075]	[−0.358, −0.084]
	Crime density, summer months	0.026 (0.023)	0.030 (0.026)	[−0.015, 0.083]	[−0.008, 0.085]
Mental Distress	Parcel maintenance	−0.177 (0.130)	–	[−0.445, 0.070]	–
	Fear of crime	0.375 (0.056) ***	0.388 (0.058) ***	[0.251, 0.475]	[0.263, 0.492]
	Victimization	0.135 (0.029) **	0.136 (0.027) ***	[0.078, 0.192]	[0.081, 0.187]
	Disadvantage index	0.027 (0.028)	0.029 (0.027)	[−0.025, 0.084]	[−0.023, 0.082]
	Population density	−0.022 (0.022)	−0.037 (0.025)	[−0.078, 0.021]	[−0.086, 0.010]
	Years residing	−0.018 (0.029)	−0.018 (0.028)	[−0.073, 0.037]	[−0.072, 0.038]
	% White	0.224 (0.064) ***	0.218 (0.066) ***	[0.098, 0.345]	[0.100, 0.357]
	% Female	0.125 (0.063)	0.122 (0.061) *	[−0.004, 0.241]	[0.001, 0.244]
	% > 65	−0.214 (0.074) **	−0.221 (0.070) **	[−0.361, −0.075]	[−0.358, −0.084]
	Crime density, summer months	0.026 (0.023)	0.030 (0.023)	[−0.015, 0.083]	[−0.008, 0.085]
	Direct effect	−0.316 (0.142) *	–		
	Indirect effect	−0.139 (0.050) ***	−0.139 (0.055) **		

Standard errors are in parentheses.

* $p < 0.05$;

** $p < 0.01$;

*** $p < 0.001$.

Table 4

Fit statistics for all models

	R-square		Variance (SE)						
	Fear of Crime	Mental Distress	Fear of Crime	Mental Distress	Chi-square (DF)	Chi-square change (DF)	CFI/TLI	SRMR	RMSEA [90% CI]
Model 1 - Multiple Regression	–	0.266	–	0.563 (0.040)	–	–	–	–	
Model 2 - Mediation Model [0.039,0.101]	0.122	0.239	0.499 (0.031)	0.581 (0.044)	24.636 (8)***		0.907 / 0.779	0.023	0.069
Model 3 - Path Model [0.038,0.097]	0.122	0.236	0.500 (0.030)	0.582 (0.044)	26.644 (9)***	2.008 (1)	0.901 / 0.792	0.024	0.067

Degrees of freedom are in parentheses. Chi-square change is n.s.

* $p < 0.05$;

** $p < 0.01$;

*** $p < 0.001$.