The Impact of Green Stormwater Infrastructure Installation on Surrounding Health and Safety

Michelle C. Kondo, PhD, Sarah C. Low, MS, Jason Henning, PhD, and Charles C. Branas, PhD

Objectives. We investigated the health and safety effects of urban green stormwater infrastructure (GSI) installments.

Methods. We conducted a difference-in-differences analysis of the effects of GSI installments on health (e.g., blood pressure, cholesterol and stress levels) and safety (e.g., felonies, nuisance and property crimes, narcotics crimes) outcomes from 2000 to 2012 in Philadelphia, Pennsylvania. We used mixed-effects regression models to compare differences in pre- and posttreatment measures of outcomes for treatment sites (n = 52) and randomly chosen, matched control sites (n = 186) within multiple geographic extents surrounding GSI sites.

Results. Regression-adjusted models showed consistent and statistically significant reductions in narcotics possession (18%–27% less) within 16th-mile, quarter-mile, half-mile ($P < .001$), and eighth-mile ($P < .01$) distances from treatment sites and at the census tract level ($P < .01$). Narcotics manufacture and burglaries were also significantly reduced at multiple scales. Nonsignificant reductions in homicides, assaults, thefts, public drunkenness, and narcotics sales were associated with GSI installation in at least 1 geographic extent.

Conclusions. Health and safety considerations should be included in future assessments of GSI programs. Subsequent studies should assess mechanisms of this association. (*Am J Public Health*. Published online ahead of print January 20, 2015: e1–e8. doi:10.2105/AJPH.2014.302314)

Exposure to trees, vegetation, nature, or green space in urban areas has been connected with multiple public health benefits, including reduced mortality,[1–3] morbidity,[4] stress, and mental fatigue.[5–7] In addition, a growing body of research has investigated the relationship between urban nature and public safety, although with mixed results. Multiple studies have found that dense vegetation may promote crime by providing criminals a place to hide themselves or illegal goods.[8–10]

Other studies have found that urban nature is associated with reduced crime. As a broad measure of urban nature, vegetation abundance has been linked to reductions in violent crimes, property crimes,[11] assault, robbery, and burglary.[12] Other studies have used more specific measures. For example, larger crown spreads of street trees and residential lot trees have been associated with fewer total crimes, property crimes, and vandalism.[3,13] Another study found that increased tree canopy cover was associated with reduced incidents of shooting, theft, robbery, and burglary, especially on public lands.[13] A study of the cleaning and greening of vacant lots found significant reductions in gun assaults and vandalism.[14]

One challenge in interpreting these studies for management purposes is that they often use coarse measures of both nature and safety. Public safety outcomes have traditionally emphasized measures such as total crimes, violent crimes, and property crimes. Few have investigated the effects of urban nature on specific crimes or health behaviors such as drug use and possession, illegal dumping, vandalism, and public drunkenness and disorderly conduct. In addition, with few exceptions,[11,14,15] previous studies have not applied an experimental or quasiexperimental approach to test whether urban greening can improve health and safety.

Little is known about the mechanism of association between urban nature and crime. The broken windows theory[16] holds that disordered and disinvested urban environments promote criminal activity. Blighted urban environments like this can erode a sense of mutual regard among residents and passers-by, signaling that no one cares and that illegal activity will be tolerated in a space.[16,17] Greened, openly visible, and ordered spaces may contribute to defensible space, indicating territory, surveillance, and care for a space, which may reduce opportunities for violence and crime.[18–20]

Other mechanistic pathways that may connect urban nature and crime are social cohesion and psychosocial stress. Environmental factors, such as vacancy, physical decay, noise, pollution, and crowding, can provoke a physiological stress response that can aggravate aggression and violence.[21] Green space may help prevent and mitigate stress, anxiety, and depression.[22,23] Access to green views has been shown to reduce mental fatigue and improve coping with stressful urban environments.[5,6] Greening has also been associated with a stronger sense of safety and feeling of security.[15]

Green stormwater infrastructure (GSI) is an emerging form of urban greening initiative in the United States and other countries. Approximately 700 cities across the United States have outdated combined sanitary and storm sewer systems that are subject to overflow during heavy rain events.[24] The US Environmental Protection Agency estimates that 850 billion gallons of combined sewer overflow discharge occurs each year in the United States. State and federal regulations, in addition to concerns about public health, ecosystem health, and climate change, have put cities under mandate to reduce combined sewer overflows.

Compared with traditional "gray" approaches such as installing separate stormwater drainage systems, GSI approaches are increasingly seen as less expensive alternatives to reducing combined sewer overflow. These GSI approaches refer to a variety of in-ground installments that allow infiltration, evapotranspiration, and capture and use or reuse of stormwater.[25] GSI has largely been implemented on a small scale and in conjunction with new development or redevelopment projects.

A lack of legislative or regulatory support has been a barrier to the broader implementation of alternative stormwater management strategies.[26] However, in April 2007, the Environmental Protection Agency signed a statement of intent supporting and encouraging the municipal use of GSI to meet federal regulatory standards. With these new federal standards, some municipalities, such as Philadelphia, Pennsylvania (population 1 547 607), have begun to plan for or implement GSI citywide.

Environmental benefits are a main driver of the GSI approach. GSI installments and other urban vegetation have been shown to be effective at reducing stormwater flows and improving stormwater quality,[27] reducing the heat island effect,[28] and improving air quality.[29] Economic benefits are also a key driver for cities' decisions to invest in GSI and other green space remediations; for instance, proximity to urban parks[30] and street tree plantings[31] can increase property values.

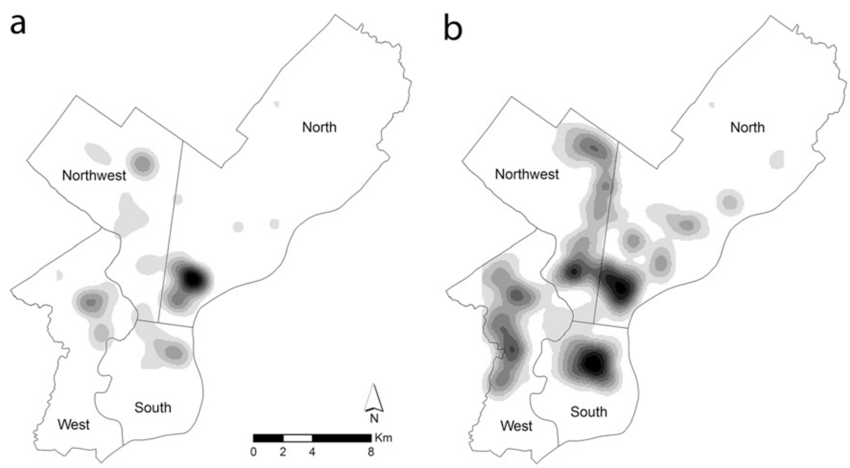
Another main impetus for Philadelphia's approach is what the city refers to as the "triple bottom line"[32]: that investment in GSI not only helps meet environmental engineering standards but has social and economic benefits as well. The greening of urban hardscape, or replacing gray impervious surface with green or otherwise pervious surfaces, is expected to improve health and safety conditions, but limited evidence supports this. Because the city of Philadelphia undertook one of the largest GSI efforts in the United States, an opportunity arose to study the impact of this program on health and safety. We therefore sought to fill various gaps in knowledge by testing the effects of GSI installments on health and safety across Philadelphia using a difference-in-differences analysis technique similar to that used in a previous observational study of vacant lot greening in Philadelphia.[14] Although our study used similar methods, the programmatic and treatment aspects of GSI and vacant lot greening are quite different. Vacant lot greening functions as a public–private venture that reproduces the same low-cost aesthetic cleaning and greening treatment of vacant lots that on average measure 1000 square feet. On the other hand, the primary goal of GSI projects is stormwater recapture, there are a variety of GSI treatments, and surface elements of GSI projects are typically much smaller than 1000 square feet. The difference-in-differences methods we employed allowed us to uniquely study and isolate the effects of these GSI projects.

METHODS

In 2000 the City of Philadelphia began installing GSI facilities everywhere except some areas of northeast Philadelphia that have separate storm sewer systems. Potential project sites are identified via petitions, requests, and concurrent projects and are selected on the basis of feasibility and cost-effectiveness analyses. At the time of our study, the city had completed construction at 52 sites (which we defined as our treatment group), whereas 186 sites were eligible for construction and in a design phase (which we defined as our untreated wait list control group). Constructed facilities receive maintenance (e.g., weeding, trash and sediment removal) at least once per year and as frequently as once per month. We analyzed the effect of treatment (i.e., project construction) between years 2000 and 2012 on nearby health and safety outcomes. We compared these outcomes to those at matched control locations from the untreated wait list design phase group.

Using procedures similar to those used in a previous study[8] to control for confounding variables related to geography or section location, we randomly selected and matched treated sites to untreated control sites within each of 4 city sections (Figure 1): northwest (13 treatment and 47 control sites), north (21 treatment and 54 control sites), south (8 treatment and 33 control sites), and west (10 treatment and 51 control sites). These 4 city sections encompass all of Philadelphia. Projects were dispersed throughout the parts of the city with combined sewer systems (all areas except the upper northeast section).

Within each city section, we randomly matched treatment and control sites. We used a common 1-to-many treatment–control matching scheme[8,33] in which we matched each treatment site with multiple control sites. Within each city section, the number of sites and the ratio between treatment and control lots varied between 1 to 3 and 1 to 6. These ratios varied according to the available number of wait list control sites in each section of the city. We did not use matching criteria to retain all treatment sites and the highest matching ratios. However, we did restrict matched pairs to those greater than a quarter-mile distance to



Note. Shading indicates a higher density of project sites. Kernel size is 300 feet. Specific project locations are not shown and densities are not defined because of privacy concerns. Green stormwater infrastructure projects are constructed only in areas with combined sewer system, which excludes a part of north Philadelphia.
Source. Data were from the Philadelphia Water Department, 2013.

FIGURE 1—Kernel density map of (a) green stormwater infrastructure treatment and (b) control sites: Philadelphia, PA, 2000–2012.

avoid a contamination effect. The pretreatment period (for both treatment and randomly matched controls) included the year in which the project was constructed and previous years. The mean pretreatment and posttreatment periods for GSI projects was 8 years and 4 years, respectively.

Data

The Philadelphia Water Department provided data on 238 GSI projects, including name, location (in latitude–longitude coordinates), date of construction, phase of design or construction, and project type. With technological development, the city has been able to design and build multiple types of GSI projects, as defined in Table 1 and shown in Figure 2.

Some locations hosted multiple project types—for example, tree trenches were often coupled with pervious pavement (Figure 2). Our data set included 152 tree trenches, 46 infiltration or storage trenches, 43 rain gardens, 29 pervious pavement installments, 20 bumpouts, 14 bioswales, 5 stormwater basins, 1 wetland, and 12 classified as other (Figure 2).

Streets and sidewalks constitute impervious surfaces and are therefore a large source of stormwater runoff. GSI is typically installed as mitigation in or near streets to capture runoff from these sources (Figure 2). Most (88%) of Philadelphia's GSI projects are at street side—immediately adjacent to or within 10 feet of the street.

The Philadelphia Police Department provided dates and latitude–longitude coordinates for 14 classes of crimes occurring between 2000 and 2012, including homicides, all aggravated assaults, aggravated assaults with guns, thefts, burglaries, disorderly conduct, illegal dumping, public drunkenness, all robberies, robberies with guns, vandalism, and narcotic manufacture, sales (i.e., distribution), and possession (i.e., with intent to use). We also used calculated aggravated assaults without guns and robberies without guns as control crime outcomes.

The Public Health Management Corporation provided health data from its Southeastern Pennsylvania Household Health Survey (available at http://www.phmc.org/chdb). This survey is conducted every 2 years with approximately 5000 Philadelphia residents (different each year) via random digit dialing. Data from respondents in the 2000, 2002, 2004, 2006, 2008, and 2010 surveys are available at the zip code level. We used adjusted estimates for census tracts, which we created using small area estimation and balancing weight techniques.[34] We interpolated values for years between surveys as the average values for the years immediately before and after the estimated year.

We used responses to questions regarding blood cholesterol, blood pressure, and stress. An answer of yes to the question "Have you ever been told by a doctor or other health professional that you have high cholesterol?" indicated high blood cholesterol. An answer of yes to the question "Have you ever been told by a doctor or other health professional that you have high blood pressure or hypertension?" indicated high blood pressure. We defined high stress to be an answer at or above 7 to the question "Using a scale from 1 to 10, where 1 means 'no stress' and 10 means 'an extreme amount of stress,' how much stress would you say you have experienced during the past year?"

We obtained demographic information at the census block group and tract levels from the Decennial Census Bureau (http://factfinder.census.gov). We assigned estimates from the 2000 Decennial Census to years 2000 to 2004, estimates from the 2005–2009 American Community Survey to years 2005 to 2009, and estimates from the 2010 Decennial Census (US Census Bureau 2010) to years 2010 to 2012. We sought demographic indicators that could influence the health status of residents and crime incidence or indicate confounding covariates associated with income and sociodemographic transition, including (1) percentage of the population aged 15 to 24 years, (2) percentage of the population aged 25 years and older with less than a high school–level education, (3) percentage of the population living below 100% of the federal poverty level (as defined by the Office of Management and Budget's Statistical Policy Directive 14 and applied by the 2000 US Census Bureau [https://www.census.gov/hhes/povmeas/methodology/ombdir.html]), and (4) median annual household income.

We calculated demographic measures and health and crime outcomes in the areas surrounding each GSI project for each year of the study using ArcGIS, version 10.1 (ESRI, Inc., Redlands, CA). Instead of choosing 1 geographic boundary, we chose to compare effects at multiple scales on the basis of practical and theoretical knowledge of likely spheres of influence. Around point-based project locations, we calculated outcomes at a sixteenth-mile distance, representing approximately 1 city block, and an eighth-mile distance, which is commonly used as the sphere of influence within Philadelphia's restrictive zoning ordinances. We also included quarter- and half-mile scales. In addition, we estimated outcomes at census block group and tract levels. Although it is assumed that the most significant

TABLE 1—Green Stormwater Infrastructure Project Type Definitions: Philadelphia, PA, 2000–2011

Type	Definition
Basin	A basin or depression that is vegetated with mowed grass.
Bumpout	A vegetated curb extension that intercepts street and sidewalk flow along the curb line.
Infiltration or storage trench	A subsurface structure designed to infiltrate or detain and release stormwater runoff.
Pervious paving	A hard permeable surface commonly composed of concrete, asphalt, or pavers.
Planter	A structure filled with soil media and planted with vegetation or trees. They can be designed below or above street grade and often contain curb edging.
Rain garden	A vegetated area typically integrated into landscape features (e.g., median strips).
Swale	A channel designed to convey stormwater. It can be designed to attenuate or infiltrate runoff where feasible.
Tree trench	A system of trees connected by a subsurface infiltration or storage trench.
Wetland	A vegetated basin that typically holds runoff for > 72 h, designed for pollutant removal.

Source. Green City, Clean Waters Implementation and Adaptive Management Plan, December 2011.[46]
Note. All project types are designed to infiltrate or detain and release stormwater runoff when necessary or feasible.

Note. Infiltration and storage trenches (not pictured) are belowground and are often colocated with other features.
Source. Photographs taken by Rebecca Schwartz.

FIGURE 2—Photograph illustrations of green stormwater infrastructure project types: Philadelphia, PA, 2000–2011.

effects will be seen at a smaller scale surrounding treatment sites, few previous studies have compared model fit at different geographic scales (with some exceptions[6]).

Nine control sites had buffers that extended beyond the city boundary, and we therefore excluded these sites. We used a kernel density method to estimate census demographic and health measures at each project site. We then attached health outcomes to census tract centroids and used these to create inverse distance–weighted measures at each site (using a cell size of 100 feet and search radius of 12 points). For demographic measures, we used the same process but generated inverse distance–weighted measures at the block group and tract levels. For crimes, we generated counts of incidents within each geographic extent for each GSI treatment and control site.

Statistical Analyses

We completed data analyses using Stata 13 (StataCorp LP, College Station, TX). We first conducted unadjusted analyses using summary statistics, cross-tabulations, and tests for normality and multicollinearity. Multicollinearity was minimal (all variance inflation factors < 3.0). Skewness tests confirmed that all outcome data were non-normal. We used a log transformation to address heteroscedasticity in the crime counts and health measures.

We used linear mixed effects models to conduct regression-adjusted analyses to assess for impact of GSI project construction on health and safety outcomes while controlling for demographic variables. We estimated parameters using 1-way random effects models using the Stata procedure XTREG. We constructed the units of observation GSI projects (i) per year of the study (t). The variable of interest was a difference-in-differences term, $P_{it} \times R_{it}$, with P_{it} indicating preconstruction (0)/postconstruction (1) status and R_{it} indicating control site (0)/treatment site (1) status. The b_3 coefficient of the difference-in-differences term estimates the effect of the treatment on the outcome.[35]

Each regression model (equation 1) included a health or safety outcome, Y_{it}; a pre–post construction term, $b_1 P_{it}$; a treatment-control term, $b_2 R_{it}$; a difference-in-differences term, $b_3(P_{it} \times R_{it})$; a term indicating time, $b_4 t$; a preperiod mean outcome interaction term to adjust for regression to the mean, $b_5 M_i$; a series of p independent demographic covariates, $b_k X_{it}$; a matched group-level random effects parameter, ξ_i; and residual error, ε_{it}. We restricted demographics covariates to pretreatment levels to control for regression to the mean.

$$(1)\quad Y_{it} = b_0 + b_1 P_{it} + b_2 R_{it} + b_3(P_{it} \times R_{it}) + b_4 t + b_5 M_i + \sum_{k=4}^{p} b_k X_{it} + \xi_i + \varepsilon_{it}.$$

We used averaged R^2 values from regression models at each geographic scale to compare fit as a method of cross-validation.[36]

P values of less than .01 indicated significant effect. We used this lower P value to account for multiple testing issues, that is, by chance alone 5% of the associations we tested could have been statistically significant.

Spatial autocorrelation, or the possibility that sites' proximity actually explained the similarities in effects, was a potential issue in our data. If present, spatial autocorrelation could lead to inaccurate coefficient or SE estimates.[37] We tested for the presence of spatial autocorrelation by generating residuals from a single linear regression model on a simplified data set of average counts of crimes with significant difference-in-differences effects found in regression models. We used crime statistics estimated at the geographic scale that were found to be most significant in model cross-validations. For regression residuals, we evaluated the nature and extent of spatial clustering in our observations by calculating Global Moran's I, using ArcGIS software, as an indicator of spatial association. We derived the spatial weights matrix generated for each site from the inverse distance spatial relationship. We calculated z score and P values on the basis of the sample size and variance. A statistically significant P value indicates a rejection of the null hypothesis that outcome measures are randomly distributed.

RESULTS

Control sites were not statistically different from treatment sites in terms of percentage of the population aged 15 to 24 years (median values were 14% and 15% for control sites and treatment sites, respectively), median household income ($27 995 and $30 551), and percentage of households earning less than the federal poverty standard (27% for both). The median percentage of the population with less than a high school–level education was lower at treatment sites (28%) than at control sites (30%), a statistically significant difference ($P < .01$). However, all these sociodemographic variables served as covariates in our final regression models.

Several crime outcomes were significantly reduced for the postperiod treatment group in the unadjusted model (data available as a supplement to the online version of this article at http://www.ajph.org). Table 2 shows that average model R^2 values were lower on average for models at the census block group level ($R^2 = 0.45$) than eighth-mile ($R^2 = 0.48$), census tract level ($R^2 = 0.65$), quarter-mile ($R^2 = 0.69$), and half-mile ($R^2 = 0.80$) distances.

Regression-adjusted difference-in-differences coefficient estimates from the mixed effects model, controlling for random effects by

TABLE 2—Adjusted Difference-in-Differences Estimates of the Impact of Green Stormwater Infrastructure Construction on Health and Safety Outcomes at 5 Scales: Philadelphia, PA, 2000–2011

	1/16-Mile Buffer		1/8-Mile Buffer		1/4-Mile Buffer		1/2-Mile Buffer		Census Block Group		Census Tract	
Outcome	Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2
Crimes, no.												
Assaults	0.01 (0.07)	0.40	0.02 (0.06)	0.67	−0.05* (0.04)	0.86	−0.03 (0.04)	0.94	0.09 (0.10)	0.50	0.04 (0.06)	0.82
Assaults with guns	0.00 (0.12)	0.30	0.1 (0.09)	0.45	0.00 (0.05)	0.74	−0.04 (0.04)	0.88	−0.18 (0.09)	0.38	0.02 (0.06)	0.74
Assaults without guns	−0.02 (0.06)	0.26	−0.06 (0.07)	0.55	−0.11* (0.05)	0.69	−0.07 (0.05)	0.72	0.00 (0.09)	0.38	0.03 (0.07)	0.66
Thefts	0.11 (0.08)	0.66	0.07 (0.04)	0.82	0.06 (0.03)	0.91	0.05 (0.03)	0.95	0.17* (0.08)	0.68	0.04 (0.05)	0.80
Burglaries	0.03 (0.06)	0.32	−0.09 (0.06)	0.52	−0.05* (0.03)	0.77	−0.06** (0.02)	0.89	0.11 (0.08)	0.40	−0.03 (0.06)	0.73
Disorderly conducts	0.04 (0.06)	0.47	−0.13 (0.13)	0.47	−0.10 (0.11)	0.62	−0.04 (0.07)	0.79	−0.17 (0.11)	0.43	0.01 (0.10)	0.53
Homicides	0.09* (0.04)	0.57	0.07 (0.06)	0.29	0.07 (0.06)	0.32	−0.04 (0.05)	0.57	−0.05 (0.06)	0.39	−0.14 (0.08)	0.33
Illegal dumping	0.01 (0.03)	0.37	0.03 (0.06)	0.33	0.00 (0.07)	0.44	−0.12 (0.06)	0.60	−0.04 (0.10)	0.35	−0.07 (0.07)	0.34
Public drunkenness	0.05 (0.04)	0.64	0.05 (0.10)	0.44	0.15 (0.15)	0.44	0.19* (0.09)	0.50	−0.06 (0.11)	0.41	0.17 (0.12)	0.36
Robberies	−0.02 (0.08)	0.46	0.02 (0.10)	0.17	−0.02 (0.03)	0.85	−0.02 (0.02)	0.94	−0.04 (0.09)	0.55	0.00 (0.04)	0.80
Robberies with guns	−0.01 (0.06)	0.30	−0.08 (0.06)	0.47	−0.05 (0.04)	0.71	−0.03 (0.02)	0.87	−0.07 (0.07)	0.37	−0.06 (0.05)	0.70
Robberies without guns	−0.11 (0.07)	0.33	−0.05 (0.07)	0.52	−0.01 (0.05)	0.67	−0.04 (0.03)	0.73	−0.04 (0.08)	0.45	0.03 (0.05)	0.65
Vandalism	0.01 (0.07)	0.48	0.04 (0.10)	0.25	−0.04 (0.03)	0.90	0.00 (0.02)	0.95	0.06 (0.07)	0.52	0.02 (0.04)	0.79
Narcotic manufacture	0.09 (0.09)	0.44	−0.06 (0.11)	0.49	−0.21*** (0.06)	0.67	−0.15** (0.05)	0.84	−0.17 (0.10)	0.39	−0.20* (0.08)	0.68
Narcotic possession	−0.26*** (0.08)	0.43	−0.27** (0.09)	0.61	−0.27*** (0.07)	0.77	−0.18*** (0.05)	0.87	−0.18 (0.11)	0.54	−0.19** (0.07)	0.74
Narcotic sales	−0.13 (0.09)	0.48	0.06 (0.10)	0.60	−0.15* (0.07)	0.74	−0.10 (0.06)	0.86	−0.04 (0.14)	0.50	−0.12 (0.10)	0.74
Health outcomes, %												
High cholesterol											0.03 (0.02)	0.95
High blood pressure											0.02 (0.02)	0.91
High stress[a]											−0.01 (0.05)	0.58

Note. Coefficients indicate relative change.

[a]We defined high stress to be an answer at or above 7 to the question "Using a scale from 1 to 10, where 1 means 'no stress' and 10 means 'an extreme amount of stress,' how much stress would you say you have experienced during the past year?"

*P < .05; **P < .01; ***P < .001.

randomly matched group, showed statistically significant reductions in certain crime outcomes with GSI project construction. Our models showed consistent and statistically significant reductions in narcotics possession at the sixteenth-, quarter- and half-mile distances from treatment sites ($P<.001$) and at the eighth-mile distance and census tract level ($P<.01$). The statistically significant findings are largely consistent across different geographic buffers and administrative units for narcotics possession, and the P values are often very small ($P<.001$), suggesting that these findings are less likely because of chance or the multiple comparisons that we tested. We found that narcotics possession after GSI construction at treatment sites was between 18% and 27% lower than at matched control sites (Table 2). By contrast, there was a citywide 65% increase in narcotics possession between 2000 and 2012.[38]

Narcotics manufacture decreased at the quarter-mile distance (21%; $P<.001$), half-mile distance (15%; $P<.01$), and census tract level (20%; $P<.05$). Burglaries reduced at the half-mile distance (6%; $P<.01$) and the quarter-mile distance (5%; $P<.05$) from project sites. Other crime outcomes (homicides, assaults, thefts, public drunkenness, and narcotics sales; $P<.05$) showed nonsignificant reductions, not consistent at multiple scales (Table 2).

Difference-in-differences estimates showed nonsignificant relative increases in the percentage of residents reporting high blood pressure and high cholesterol and decrease in high stress at the census tract level.

In addition, we tested for spatial clustering in our observations on a simplified model of burglaries and narcotics manufacture and possession at the half-mile level. The most significant Global Moran's I statistic calculated from our regression model residuals was 0.36 with a z score of 0.99 ($P=0.32$), suggesting that spatial autocorrelation was not an issue.

DISCUSSION

Cities, including Philadelphia, are promoting new GSI programs in the hopes that GSI results in economic and health benefits that traditional gray infrastructure does not. Philadelphia is one of the first cities to adopt a GSI approach to stormwater management on a citywide scale. One possible mechanism for the creation of additional benefits is that GSI can be viewed as green exposure, which has been shown to reduce violence, aggression, assaults, and vandalism and lessen crime in general.[3,5,6,13,14] Yet the specific effect of GSI installment on surrounding health and safety has not been tested.

Our study indicates that Philadelphia's GSI program has had an effect on safety in nearby areas. Our models found significant reductions in certain crimes over an average 4-year follow-up period, indicating that a relatively long-term impact might be expected. We found that construction of GSI projects was associated most strongly and consistently with reductions in occurrence of narcotics possession. Possession indicates the buying as opposed to the selling of narcotics. We did not test the specific mechanisms underlying this association; however, previous theories and empirical studies provide excellent insight into these mechanisms as well as hypotheses to test in future studies.

For example, GSI projects on streets, sidewalks, and adjoining open spaces may contribute to a defensible environmental design[39] or space,[18–20] indicating that a block is communal territory, is cared for, and is surveilled and is therefore a less than ideal public place to purchase and possess illegal drugs. In Philadelphia, buyers often travel along streets looking for dealers and for undersurveilled places to buy.[40] It is important to note that although narcotics possession represents a serious social incivility, we did not find any association between GSI installation and more serious crimes such as aggravated assaults and gun assaults, which have been established with other greening programs.[14,41]

In addition, previous studies have found influences of both social network and neighborhood characteristics on illegal substance use.[42] However, studies have commonly used various measures of neighborhood socioeconomic status as indicators of neighborhood influence on drug use.[42–44] Some studies have found links between drug use and subjective measures of "neighborhood disorder"[45] or objective measures such as the percentage of vacant housing.[44] Further studies examining the connection between drug use and urban greening are warranted.

Arrests for narcotics manufacture and burglaries were also significantly reduced at 1 or more geographic levels. To a lesser degree, there were also reductions in thefts and assaults. These findings support the broken windows theory: that crimes (in this case narcotics possession and manufacture and burglaries) are less likely to be committed in areas that appear to be cared for well.[17,16] This finding also raises questions regarding potential effects of project type and maintenance on health and safety outcomes.

Although some studies have shown reduced mortality with increased exposure to green space,[1,2] health outcomes in this study were not strongly correlated with GSI installation. Results showed a negative, nonsignificant effect on stress levels. There was also a nonsignificant association between project construction and the increased reporting of high blood pressure and cholesterol. These findings suggest that further research is necessary, perhaps with more localized health survey data or more precise health measures.

Limitations

Although both public and private developers have installed GSI in Philadelphia, we considered only public GSI installments. Private installments should be considered in future studies. In addition, the effects of GSI on health and safety may be specific to project type, although we were not able to test this because of sample size limitations.

We used administrative data and boundaries, which are potentially problematic. First, there are known limitations to the Public Health Management Corporation household health survey data. This survey was conducted only every 2 years, surveyed housed residents, had a low response rate, and was not designed for small area estimates. Better measures of health outcomes would yield more accurate estimates of GSI's effect on health.

Second, the use of boundaries, including census tracts or block groups, to measure health and safety outcomes associated with each project is potentially problematic. These boundaries are often shaped irregularly, and projects are rarely centered within each boundary. We were able to adjust for this problem among demographic predictor variables by using the inverse density weighting and kernel density methods; however, health outcomes are represented by counts at administrative (census tract) levels. Point-based distance estimates (i.e., buffers) offer a more accurate way to quantify density of safety outcomes associated with a project site. To address this issue, we did not assume the optimal geographic scale at which to estimate effects but instead compared effects at multiple scales using model fit statistics.

Nevertheless, model fit did not align by estimate geography. We assumed that the highest effect would be nearest to the treatment site. One explanation that should be tested is whether there is a spillover effect of positive influence from these sites. Three additional questions that emerged are (1) whether the discovered effect indicates displacement of such activity or spillover effects in surrounding areas; (2) whether the presence of construction crews influences GSI's effect on health and safety outcomes; and (3) whether health and safety effects hold in relation to additional counterfactual or control outcomes, such as crimes or aspects of crimes not plausibly related to greening, or outcomes completely unrelated to health and safety.

Conclusions

Philadelphia has an ambitious program to construct GSI on a citywide scale to reduce combined sewer overflows in nearby water bodies. A previous municipal assessment justifying this program suggested that it would have higher social, economic, and health benefits than would a gray infrastructure approach.[32] To date, there have been no published studies of the health and safety outcomes of GSI installation. Although numerous safety and health outcomes were found to be statistically unaffected by GSI, our analysis suggests that GSI installation may be a deterrent to the possession and manufacture of illegal drugs in public spaces. Although safety outcomes are not typically included in cost–benefit assessments of GSI programs, our findings indicate that they should be included as GSI programs such as the one in Philadelphia move forward. ■

About the Authors

Michelle C. Kondo, Sarah C. Low, and Jason Henning are with the US Department of Agriculture-Forest Service, Northern Research Station, Philadelphia, PA. Michelle C. Kondo and Charles C. Branas are also with the Center for Clinical Epidemiology and Biostatistics, Perelman School of Medicine, University of Pennsylvania, Philadelphia. Jason Henning is also with Davey Trees, Inc., Philadelphia, PA.

Correspondence should be sent to Michelle C. Kondo, PhD, USDA Forest Service, 100 North 20th Street, Suite 205, Philadelphia, PA 19103 (e-mail: michelleckondo@fs.fed.us). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints" link.

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Contributors

M. C. Kondo, S. C. Low, and C. C. Branas contributed to the study conceptualization and design. M. C. Kondo, J. Henning, and C. C. Branas contributed to the data interpretation. M. C. Kondo conducted the data analyses and led the writing and editing of the article. S. C. Low, J. Henning, and C. C. Branas contributed to the writing and editing of the article. C. C. Branas supervised the data analyses.

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Human Participant Protection

Institutional review board approval was not needed because this project involved analysis of publicly available and de-identified data.

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