Identifying Sweet Spots for Green Stormwater Infrastructure Implementation: A Case Study in Lancaster, Pennsylvania

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Abstract: Green stormwater infrastructure (GSI) can provide multiple benefits in addition to stormwater management. However, there is a need to improve GSI siting to ensure these benefits are realized. We present a planning algorithm that hones in on 'sweet spots' of GSI implementation that are hydrologically optimal, feasible, and provide more equitable access to the benefits of GSI. We apply this approach in Lancaster, a city in Pennsylvania, US, with multiple stormwater-related challenges. To identify sweet spots, we first leveraged available spatial data to derive maps of five key criteria, including hydrology, vegetation, property ownership, sewer system type, and social vulnerability. We then normalized each layer and combined them using two different weighting schemes, including an 'Even Weights' and a 'People's Choice' scenario based on a choice experiment embedded in a community survey. The survey indicated a preference for prioritizing the hydrology and sewer system criteria. Sweet spots for GSI implementation under each scenario were mapped based on the 90th percentile of the final combined key criteria layers. Comparisons between the two weighting schemes indicated a 73% overlap in sweet spot locations. We also found a small percentage (16%) of existing GSI in Lancaster overlapped with the sweet spots, indicating an opportunity to target future GSI implementation in the remaining sweet spots. Despite being demonstrated in a specific city, this relatively simple approach leveraging widely available spatial data can be applied and customized elsewhere and help improve future GSI siting methods. **DOI: 10.1061/JSWBAY.SWENG-513.**

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Introduction

Unmanaged stormwater runoff is a challenging environmental problem in urban areas, causing potential nuisance pluvial and fluvial flooding, water quality impairment, and ultimately affecting environmental health (Barbosa et al. 2012; Carson et al. 2013; Walsh et al. 2016). Population growth and climate change are likely to intensify these problems (Barbosa et al. 2012; Carter et al. 2018). In cities with combined sewer systems (CSSs), where stormwater runoff and domestic sewage are transported in the same pipe system, these problems get more complicated because even small storms can overwhelm the CSS and lead to combined sewer overflows (CSOs). CSOs release heavy loads of pollutants, such as sediments, nutrients, and pathogens, to water bodies, harming human and ecosystem health (Carson et al. 2013; Botturi et al. 2021).

Stormwater control measures are placed in the urban landscape to control the quality and quantity of stormwater runoff and can comprise varying combinations of green and gray infrastructure or ecological and technological elements (Bell et al. 2019). Green stormwater infrastructure (GSI), such as infiltration basins, green roofs, wetlands, rain gardens, and bioswales, leverages ecological components such as vegetation and soil to treat stormwater (Adhikari et al. 2023). Besides reducing runoff and pollutant loads, GSI contributes to other ecosystem services such as cooling through evapotranspiration or shading, enhancing biodiversity through habitat provision, improving aesthetics, or enhancing cultural services (Hoover and Hopton 2019; Prudencio and Null 2018). In recent decades, because of its multifunctionality, GSI has been increasing in popularity to replace or complement the services of gray infrastructure (McPhillips and Matsler 2018).

Although green infrastructure is promoted based on its multifunctionality, GSI projects are primarily sited based on stormwater abatement due to the regulatory focus on stormwater quantity and quality. Thus, much research on spatial optimization of GSI has focused on optimizing stormwater management benefits and

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hydrologic or water quality metrics at a sewershed or watershed scale (e.g., Zhang and Chui 2018). However, resource constraints and the potential for GSI to help address a wide range of urban environmental issues have made it essential to consider multiple functions and beneficiaries of GSI and identify optimal locations for their implementation (Bell et al. 2019; Meerow and Newell 2017). In the last decade, research on GSI siting has increasingly considered optimizing multiple functions beyond water quantity and quality management. For example, local microclimate regulation is one factor being considered to incorporate the benefits of vegetated spaces on urban heat island mitigation (Madureira and Andresen 2014; Marks et al. 2022; Norton et al. 2015). Habitat provision is another factor considered in optimizing the benefits of vegetated stormwater solutions (Jessup et al. 2021).

Equity in access to GSI benefits has been recently gaining attention considering documented inequity in access to GSI benefits among certain demographic groups (Baker et al. 2019; Brent et al. 2022; Chan and Hopkins 2017; Mandarano and Meenar 2017; Marks et al. 2022). Looking more broadly at green space in cities, there is also widely documented inequity in the distribution of vegetation and associated access to benefits (Wen et al. 2013; Nesbitt et al. 2019). Beyond the cooling benefits of vegetation, people living in greener or more vegetated surroundings report lower levels of fear, fewer incivilities, and less aggressive and violent behavior (Ward Thompson et al. 2012). Exposure to vegetated spaces has also been associated with many health benefits, including stress reduction and sustained mental health improvements (Alcock et al. 2014; Kuo and Sullivan 2001). Conversely, the lack of green space in people's living environment has coincided with feelings of loneliness and a perceived shortage of social support (Maas et al. 2009). In dense urban areas, GSI and its associated vegetation and stormwater management function can help mitigate the social vulnerability of communities by reducing exposure to certain hazards as well as providing cultural services (Dagenais et al. 2017).

Despite the clear importance of considering who has access to the benefits of GSI, few US cities have explicitly considered environmental justice and/or social vulnerability in their GSI siting strategies (Hoover et al. 2021). To address this gap, some GSI planning strategies have integrated sociodemographic variables relevant to the benefits of GSI to improve spatial planning efforts (Mandarano and Meenar 2017), while others have implemented more complex metrics of social vulnerability or equity, generally relying on existing indices such as the social vulnerability index (SoVI) created by the Hazards and Vulnerability Research Institute (Castro 2022; Chang et al. 2021; Marks et al. 2022; Pacetti et al. 2022).

One of the most comprehensive GSI planning approaches is the Green Infrastructure Spatial Planning (GISP) Model (Meerow and Newell 2017). With green infrastructure broadly defined as including both GSI and other green spaces such as parks, the GISP is a GIS-based multicriteria method that combines six benefits of green infrastructure, including stormwater management, social vulnerability, green space provision, air quality improvement, urban heat island amelioration, and landscape connectivity. The model also incorporates stakeholder priorities from 23 green infrastructure experts in the Detroit region through a survey on the importance of the six benefit criteria. The criteria layers were then weighted based on the survey results (Meerow and Newell 2017). However, despite its many strong elements, the GISP could benefit from considering alternative hydrologic metrics and greater community input.

Here, we build upon GISP and related work by proposing a multicriteria planning approach that leverages widely available data to consider multiple GSI benefits, accessibility to those benefits, and feasibility of implementation. More specifically, we demonstrate an alternative approach for assessing runoff accumulation and flooding potential while still avoiding a data-intensive runoff routing model. Additionally, we also consider several other factors, including sewer system type (i.e. combined versus separate, to address different types of overflows), existing vegetation (to integrate multiple ecosystem services of vegetated systems), property type (to inform the feasibility of implementation), and social vulnerability (to factor in who benefits from GSI services). Moreover, to address the overemphasis of expert opinions and lack of community input in previous siting approaches, we explore how incorporating community preferences in GSI siting criteria may influence the spatial pattern of optimal locations.

Methods

In this section, we first introduce our study area and then elaborate on the four-step procedure for identifying GSI sweet spots: (1) creating five criteria layers, (2) developing two weighting scenarios, (3) combining the criteria layers under the two different scenarios, and (4) analyzing and comparing the mapping outcomes for implications.

Study Area

We conducted this research in the City of Lancaster, located in south-central Pennsylvania (Fig. 1). This historic city was incorporated in 1818 and had a 2010 population of 59,322 and an urban area of 19 sq km. The annual average rainfall is 107 cm (1926–2000) (City of Lancaster 2011). Lancaster is highly developed, with 53% of the city being impervious surfaces, such as buildings, roads, parking lots, and sidewalks (Chesapeake Conservancy 2020).

The city uses both a CSS and a municipal separate storm sewer system (MS4). The CSS covers about 45% of the city and conveys rainwater, domestic sewage, and industrial waste to the city's Advanced Wastewater Treatment Facility. During heavy rains, untreated CSOs are discharged into the Conestoga River, a tributary of the Susquehanna River (The City of Lancaster 2022), serving as the primary source of pollution for the Conestoga during wet weather. Based on the city's annual CSO status reports, on average, about one billion gallons of untreated combined sewage is discharged into the Conestoga River annually (City of Lancaster 2011).

To address this problem, Lancaster adopted its 25-year Green Infrastructure Plan in 2011, with 327 potential GSI projects identified (City of Lancaster 2011). These potential GSI projects were primarily targeted on publicly owned land in areas of the city with high impervious cover. In 2018, Lancaster entered a consent decree with the US Environmental Protection Agency and the Pennsylvania Department of Environmental Protection to comply with the Clean Water Act and Clean Stream Law. Additional GSI implementation is a major component of this agreement. Lancaster currently has about 500 GSI facilities installed to manage stormwater and associated pollutants. Their major GSI types include bioretention basins/swales, infiltration trenches, permeable pavement, tree trenches, and detention basins (City of Lancaster 2011).

Creation of Criteria Layers

Data availability, accessibility to multiple GSI benefits, and feasibility of implementation were key considerations for choosing the siting criteria. Based on discussions among the interdisciplinary project team and Lancaster City stormwater managers, five criteria

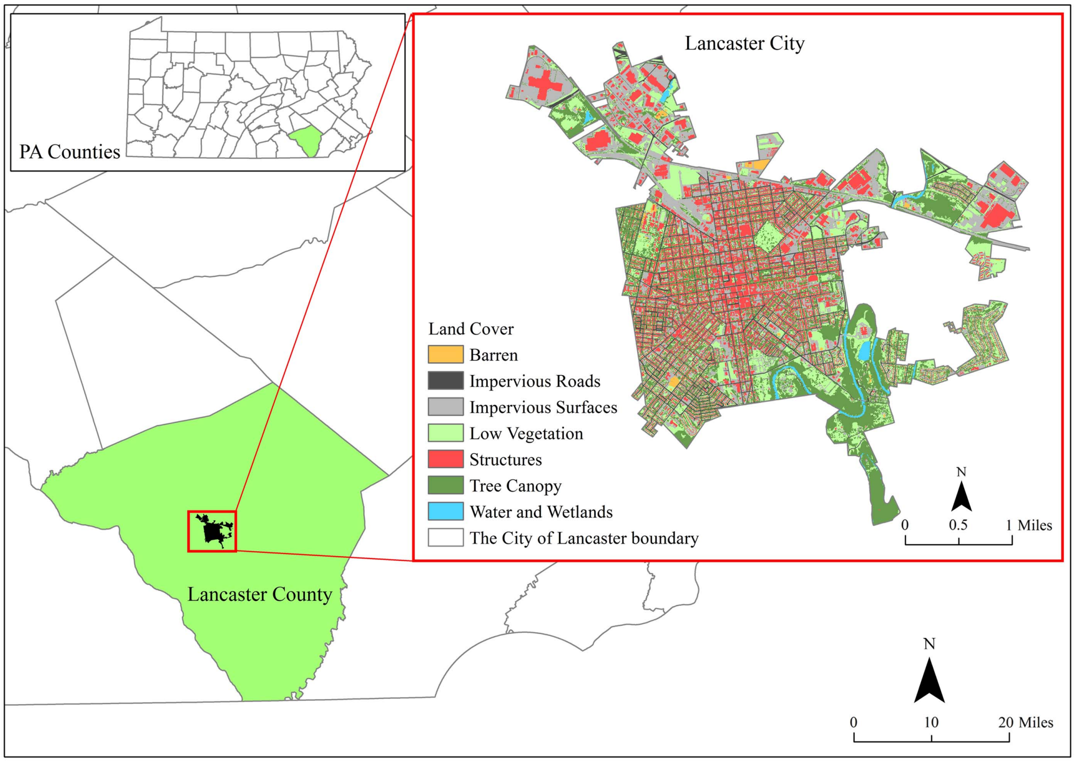

Fig. 1. Location and land cover of the City of Lancaster, PA.

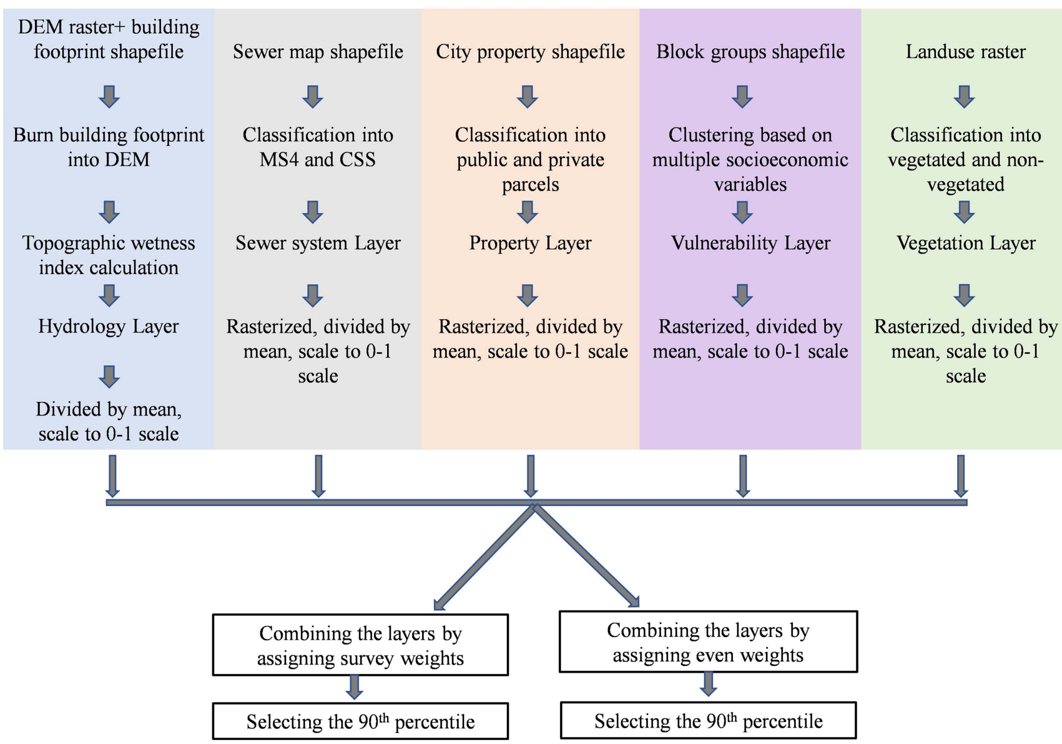

Fig. 2. Flowchart demonstrating the multi-step procedure for the sweet spots analysis.

were selected: hydrology, sewer system, green space provision, property ownership, and social vulnerability. A series of steps (Fig. 2) were then taken to create the five criteria layers, as detailed in the following section.

Hydrology Layer

The hydrology layer was created to identify areas with high potential for stormwater accumulation and, therefore, priority for GSI implementation. There are different methods for identifying such hydrologic hotspots. The most complex approaches leverage hydrologic and hydraulic models that route water through the surface landscape and drainage infrastructure. While these methods can yield high accuracy, they also require high data inputs and calibration (Rosenzweig et al. 2021). In contrast, the most simplified methods rely strongly on land cover and soil characteristics, such as the Curve Number or Rational Method (Hosseiny et al. 2020; Jessup et al. 2021; Meerow and Newell 2017). These approaches sometimes integrate simple sewer system characteristics, such as the density of sewer pipes or CSO discharge (Meerow and Newell 2017; Pacetti et al. 2022). Another type of simplified method considers topography as the most important factor controlling water movement in the landscape (Schmidt and Persson 2003), such as the 'blue spot' method and topographic wetness index (TWI). Despite the ability of urban drainage systems to mitigate flooding in low-lying areas, topography remains a strong indicator of water accumulation in urbanized areas during high-intensity storm events when typical drainage infrastructure may be overwhelmed. The 'blue spot' method detects low-lying areas (blue spots or sinks) in the landscape from analysis of a digital elevation model (DEM) and then assesses their flooding potential based on the sink's watershed and capacity (Balstrøm and Crawford 2018). The TWI is also calculated using a DEM but with simple equations considering topographic elements such as slope and flow direction (Buchanan et al. 2013; Quinn et al. 1995). TWI has long been used in hydrologic models to predict areas prone to water accumulation in rural catchments (Buchanan et al. 2013). However, recent work has demonstrated its utility as an indicator of urban pluvial flooding (Kelleher and McPhillips 2020; Metes et al. 2022).

Considering data availability and computational efficiency, we chose the TWI as an indicator of areas prone to stormwater accumulation. TWI is calculated according to Eq. (1), where a represents the upslope area and $\tan\beta$ represents the local slope. The flow direction and upslope area of a given point are calculated based on the D-infinity flow direction algorithm as it performs better than other alternatives such as the D8 and multiple flow direction methods (Kelleher and McPhillips 2020; Tarboton 1997)

$$\mathrm{TWI} = \ln\left(\frac{a}{\tan\beta}\right) \tag{1}$$

We first downloaded a 1m high-resolution DEM of Lancaster, HUC 8 watershed shapefiles, the Lancaster City boundary, and building footprints from Pennsylvania Spatial Data Access (PASDA 2018). We then clipped the DEM to the three HUC 8 watersheds containing Lancaster. After eliminating building footprints from the DEM, we calculated the TWI using the TauDEM package (Tarboton 2015) and the D-infinity flow direction algorithm in ArcGIS (v. 10.7). Next, we clipped the TWI map using the city boundary and normalized the values to the range 0–1. Finally, we removed areas of existing water bodies from the TWI map (PASDA 2007).

Social Vulnerability Layer

The social vulnerability layer was created to help prioritize GSI implementation in vulnerable communities. Here, vulnerability is defined as the inability of residents to deal with hazards such as flooding (Cutter 1996; Meerow and Newell 2017). The factors that shape social vulnerability are complex and difficult to quantify (Meerow and Newell 2017). There are different methods used for measuring social vulnerability, but income, poverty level, minority, race, ethnicity, single-parent status, vacancy, age, gender, employment status, educational attainment, and household size are among the most frequently used variables in previous studies (Cutter et al. 2003; Grabowski et al. 2023; Mandarano and Meenar 2017). For example, higher income typically reduces social vulnerability because wealth enables communities to recover quickly from hazard impacts or may lead to prioritization of infrastructure upgrades (Cutter et al. 2003). Additionally, a higher proportion of the population identifying as a racial or ethnic minority may increase social vulnerability because of historical bias or inequitable and inadequate allocation of resources, including those related to siting and maintaining critical infrastructure (Hendricks and Van Zandt 2021). Potential language barriers can also make information exchange difficult, leading to residents' inability to use resources after a disastrous event. Additionally, extremes of age (both young and elderly) can also affect social vulnerability, with mobility concerns in harmful situations, for example, for the elderly (Cutter et al. 2003).

Based on an extensive literature review, we adapted the commonly used SoVI (Cutter et al. 2003; Meerow and Newell 2017). Instead of aggregating 29 socioeconomic variables, we selected the 16 attributes with data available at the smallest scale of census blocks (a total of 74 blocks for Lancaster). The census block scale was chosen to produce fine spatial detail in the final layers. The selected variables included income, poverty, percent female, percent female in the civilian labor force, racial and ethnic minorities, median age, population under age 5, population over age 65, unemployment, renter-occupied houses, single-parent households, education, tree cover, violent crime, building vacancy, and population density (Appendix A, Table 1). Using data obtained from the 2018 US Census, the City of Lancaster, and ArcGIS online, we first performed principal component analysis (PCA) to reduce correlation and create independent factors from the 16 variables (Hastie et al. 2009). The PCA extracted five principal components that account for 75% of the variability of the data. Then, we clustered the census blocks into four groups based on the k-means method (Cutter et al. 2003; James et al. 2013) using R, the Stats package, and the k-means function (R Core Team 2020; Appendix A, Table 2). We calculated the social vulnerability indicator and assigned social vulnerability indices for the groups as 0.36, 1.7, 2.37, and 4.3 for groups 1, 2, 4, and 3, respectively.

Sewer Layer

The sewer layer, which delineates the CSS and MS4 areas in Lancaster, was included to allow different options to prioritize either CSS or MS4 for GSI implementation. One option is to prioritize the CSS area, where GSI can help reduce the runoff quantity through the CSSs after heavy rains, thus aiding the city in meeting its CSO goals in the consent decree. However, priority can also be given to implementing GSI in the MS4 area, which suffers from flooding challenges and requires improved stormwater management. In this case study, we demonstrate the option of prioritizing the CSS. If desired, this priority can also be removed by choosing a weight of 0 for the sewer layer later when integrating the five criteria. Using the sewer system shapefile obtained from the municipality, we rasterized the layer by assigning a 0 value to the MS4 area and 1 to the CSS area.

Vegetation Layer

The vegetation layer was created to classify Lancaster into vegetated and nonvegetated areas. This allows the option of prioritizing GSI in areas currently lacking vegetated space, where GSI implementation will bring critical cobenefits such as urban heat island mitigation, stormwater retention, and habitat creation

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(Melaas et al. 2016). To create this layer, we used 1m high-resolution regional land use data for the Chesapeake Bay Watershed (Chesapeake Conservancy 2020). Land use categories include impervious roads, impervious nonroad, tree canopy over impervious, water, floodplain wetlands, other wetlands, forest, tree canopy over turf, mixed open, fractional turf (small), fractional turf (med), and agriculture. After classifying the land cover layer into vegetated and nonvegetated pixels, we assigned the 0 value to vegetated pixels and 1 to nonvegetated pixels.

Property Layer

The property layer was created to allow consideration of different types of property ownership, which may impact the feasibility of GSI implementation as well as who benefits from it. Here, we prioritize public parcels based on the higher feasibility of implementing GSI and the increased number of people with access to GSI on public property. Using the property shapefile provided by the city, we categorized parcels into two groups: private versus public. Private properties include residential, private nonresidential, and vacant residential, whereas public parcels primarily include parks, schools, and municipal buildings. We then assigned a 0 value to the private parcels and 1 to the public parcels.

Developing Two Weighting Scenarios

To explore how different weighting schemes may influence the spatial pattern of the GSI sweet spots, we test two scenarios in our study. The first scenario of "Even Weights" involves weighting the five layers equally, i.e., the weight of 0.2 is assigned to every layer (Bozorg-Haddad et al. 2021). The second scenario is a "People's Choice" scenario, where the layers are weighted differently based on community preferences. We specify the survey methods used to parameterize the People's Choice scenario as follows.

Choice Experiment for Identifying Public Preference

We designed a choice experiment survey to understand the preferences of Lancaster City residents regarding GSI planning (full survey available in Supplemental Materials). Choice experiments are a type of stated preference tool typically used in economics for nonmarket valuation (Brent et al. 2017). Here, we applied this technique to discern preferences for how GSI location is prioritized. The survey included an introduction page with a GSI definition, Lancaster's GSI implementation efforts, images of GSI facilities, definitions of the five criteria used in the spatial analysis, and an explanation of the choice activities. The respondents were then randomly assigned to one of four blocks containing five separate choicesets. The choice sets were created using a simulation approach that maximized D-efficiency from the full factorial design. Each choiceset asked the respondents to select between two given GSI plans (i.e., Plan A versus B). Table 1 is an example of a choiceset. When identifying their preferred plan, the respondents needed to compare which specific criteria were prioritized under which scenario. Some may consider stormwater management as the most essential service provided by GSI, thus selecting the plan that prioritizes flood control, while others may think providing green (vegetated) spaces for vulnerable communities is more important. Analyzing the entire sample population's responses estimates the relative importance of the five criteria.

The survey was administered in Qualtrics and received an exemption from the Penn State Internal Review Board (# STUDY00016210). We sent the survey link in spring 2021 by postcards to 3,315 addresses randomly selected from the Lancaster property database. Results were analyzed in the R software using a conditional logit model as implemented in the *mlogit* package (Brent et al. 2017; Londoño Cadavid and Ando 2013). With participants' GSI plan choice as the outcome variable, this model predicts the probability of selecting the preferred GSI plan as a function of the five criteria. The estimated parameters indicate how important each criterion is when selecting the preferred GSI plan and were then used as weights for the five criteria indicating community preference for GSI siting.

Combining Criteria Layers to Identify GSI Sweet Spots

For combining the layers, we adopted a popular multicriteria decision analysis approach that leverages weighted linear combination (e.g., Meerow and Newell 2017). After the raw criteria layers were prepared, all vector layers were converted to rasters. A series of steps were then undertaken to examine layer correlations and normalize layer values before aggregating them using different weighting schemes under the two scenarios.

First, to assess redundancy in the five criteria layers, we used the "Band Collection Statistics" tool in ArcMap (v.10.7.1) to generate a correlation matrix that shows the correlation of different layers. This matrix helps to determine the presence of strong correlations that may impact the decision to include them all in the final combined layer. Because no significant correlations emerged among the individual layers (Appendix B, Table 1), all five layers were included in subsequent processing and analyses.

Second, due to the significant differences in ranges of values in different layers, it is necessary to rescale all layers to a common numerical range (e.g., 0 to 1) to avoid giving those with larger values heavier weights. We used a technique that normalizes the values based on mean and standard deviation (Bozorg-Haddad et al. 2021) so that we would not bias our 'Equal Weights' scenario by having different mean values. In order to make the mean value of all of the layers the same, we divided each criteria layer by its mean value and then scaled all the layers into 0 to 1 values (Fig. 3).

Next, we assigned appropriate weights to each criteria layer and combined them to inform priority locations for GSI implementation under the two chosen scenarios. As mentioned, the "Even Weights" scenario assigned a weight of 0.2 to every layer, while the "People's Choice" scenario applied the weights derived from the choice experiment. These weights were then multiplied by each layer, and the five values were added together to create a final combined layer with a possible range of 0 to 1 under each scenario.

Table 1. An example of a choice question asking, "Which stormwater infrastructure plan do you prefer for Lancaster City?"

Category	Plan A	Plan B
Flood control	Prioritize areas with high flood likelihood	No prioritization
Green space	Prioritize areas with the least vegetative cover	No prioritization
People	No prioritization	Prioritize most vulnerable
Sewer system type	Prioritize the combined sewer area	Prioritize separated storm sewer area
Property	No prioritization	Prioritize private property

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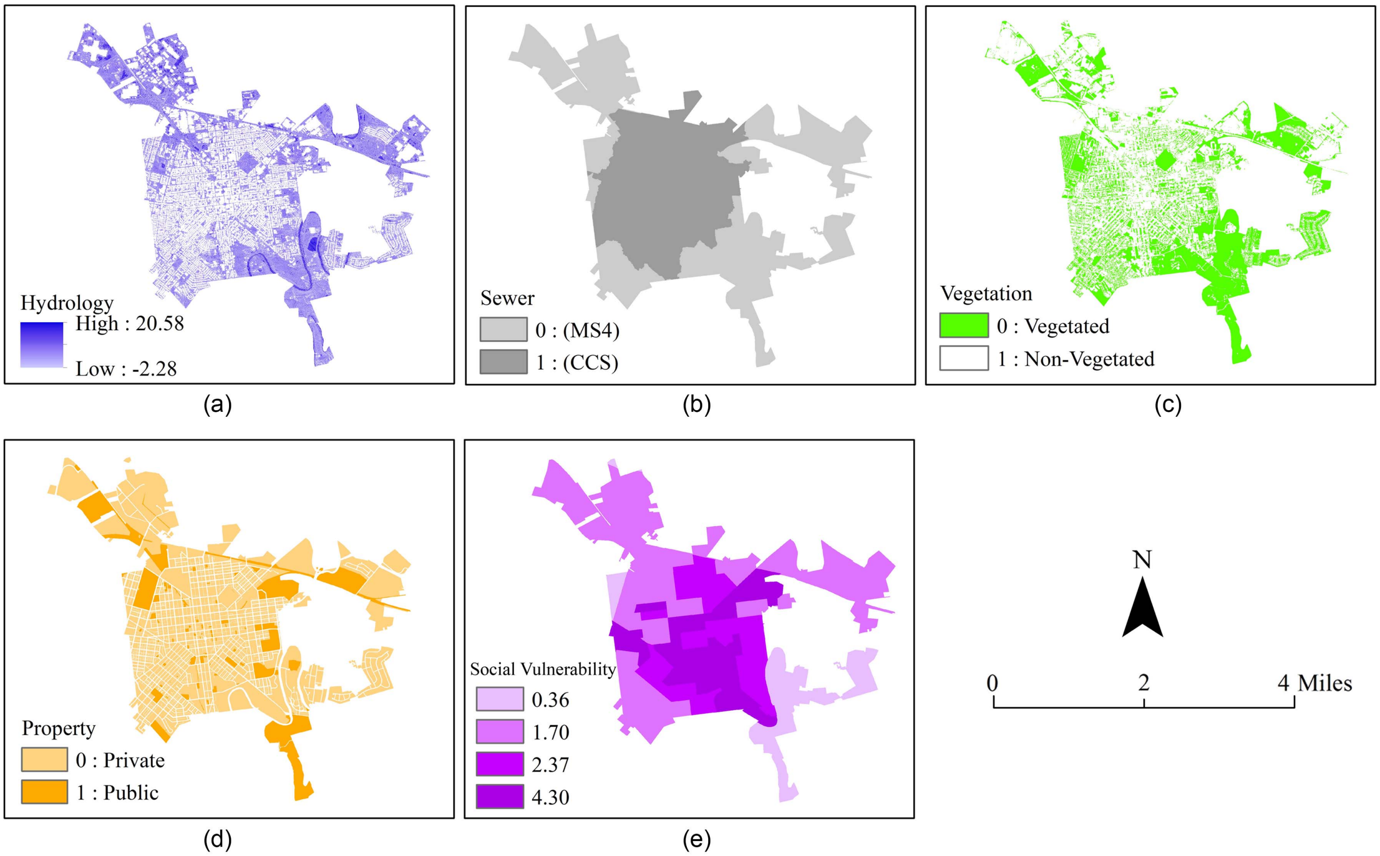


Fig. 3. Five criteria layers with original values: (a) hydrology layer; (b) sewer layer; (c) vegetation layer; (d) property layer; and (e) social vulnerability layer.

Spatial analysis was performed on the two final combined layers. Locations with the highest values were considered 'sweet spots' or high-priority locations for GSI implementation. We specifically selected the values exceeding the 90th percentile. This was an arbitrary decision to isolate the top 10 percent of values; the specific range of values in similar analyses could be selected based on local preferences and constraints. Two 90th-percentile sweet spot raster maps were extracted and converted into a vector format. The total area of sweet spots under each scenario was calculated for subsequent comparisons.

Finally, the overlaps between the two sweet spot maps and the existing GSI map were analyzed using the Intersect tool in ArcMap. Percentages of overlap of the two sweet spot maps were calculated by dividing their intersect area by the total area of sweet spots under both scenarios. Similarly, to quantify the percentages of existing GSI overlapping with sweet spots, we found the intersecting areas of each sweet spot map and the existing GSI map and calculated the percentage of existing GSI located in the detected sweet spots. We also checked the overlap of existing GSI with the hydrologic hotspots by creating a 90th-percentile hydrology layer, intersecting it with the existing GSI map, and dividing the intersecting area by the total area of existing GSI.

Results

Individual Criteria Layers

The five criteria layers show both similarities and differences in prioritized locations. First, the hydrology layer [Fig. 3(a)] indicates major variation across the city with respect to flood risk; thus, a need for prioritizing different locations for stormwater management. The TWI values in the original raster prior to normalization ranged between −2.28 and 20.58 with a mean of 4.89. A larger TWI value means the area is more prone to runoff accumulation and flooding. The hydrology map, in general, shows higher flood risk areas around the edge of the city. Second, the sewer system layer indicates that the CSS area dominates the older downtown area, comprising 45% of the city [Fig. 3(b)]. Third, the vegetation layer [Fig. 3(c)] indicates that the largest vegetated spaces are located toward the outskirts of the city, with some scattered presence of vegetation in the downtown area. Fourth, the property layer indicates a variable distribution of public and private parcels throughout the city, with some of the largest public parcels being parks [Fig. 3(d)]. Public parcels comprised 20% of the city area, while private comprised 80%. Lastly, for the social vulnerability layer, zones of increased social vulnerability are concentrated in the central downtown area, more specifically in the southeast quadrant [Fig. 3(e)].

For creating the social vulnerability layer based on the PCA, we selected five principal components because they represent 74% of the variance of all the variables analyzed. The dominant variables in these five principal components are the percentage of people living in poverty, percent female, percent of the population over 65, percent of the population under 5, and tree cover. More information about the PCA is presented in Appendix A, Tables 1 and 2.

Patterns of GSI Sweet Spots

The choice experiment survey for parameterizing the weights for the "People's Choice" scenario received 98 complete/usable

Table 2. Survey weights assigned to criteria layers

Layer name	Hydrology	Sewer	Vegetation	Public property	Private property	Social vulnerability
Weight	0.258	0.271	0.209	0.103	0	0.157

responses (3% response rate). Based on self-reporting of sociodemographic characteristics, these respondents are fairly representative of average Lancaster City residents. Age was well distributed across all categories spanning from 18 to 65+ years old. While education and income had respondents in all categories, there was the least representation for those with high school or trade school education and less than $25,000 annual household income (Appendix B, Tables 2–5). Compared to city statistics (US Census 2020), our survey had some overrepresentation of higher income levels, higher education levels, white/Caucasian ethnicity, and people over age 65; however, approximately a third of respondents did not report demographics, leaving some uncertainty in representation. The resulting weights from the choice experiment survey are reported in Table 2. The respondents put the highest priority on flood control, reduction of CSOs, and increasing green space.

The two final combined layers demonstrate similar overall spatial patterns where the highest values, thus locations to prioritize GSI implementation, are concentrated in the downtown city center (Fig. 4). The downtown area has most of the priority implementation areas for both weighting schemes. Fig. 5 shows the 90th percentile map of combined layers with the even weighting of criteria layers [Fig. 5(a)] and the assigned survey weights [Fig. 5(b)].

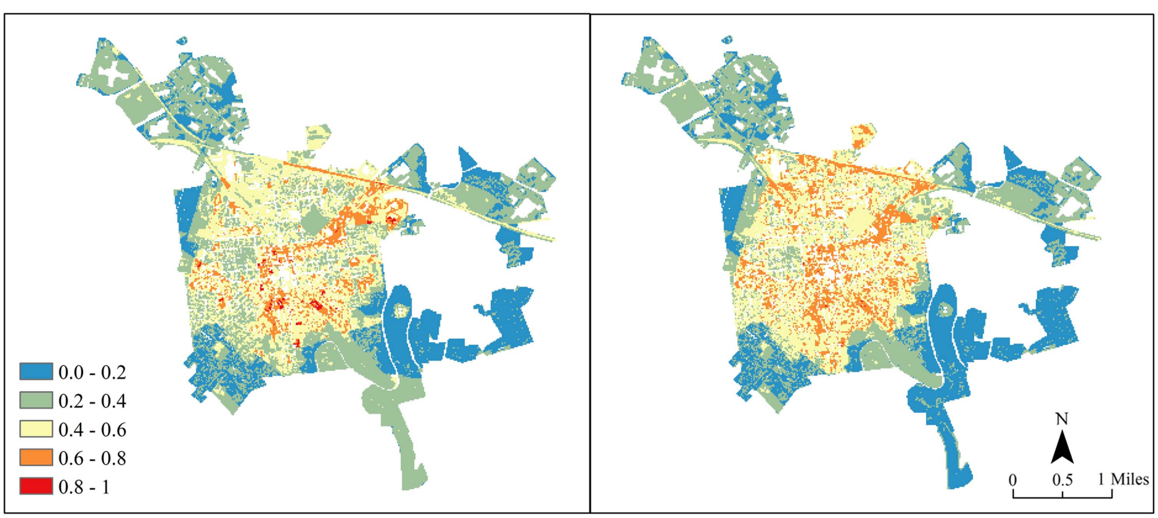
The two 90th-percentile sweet spot maps under the two weighting schemes show a substantial overlap. After weighing and combining five criteria layers with two approaches (even versus People's Choice), we found a significant overlap (72%–74%) between the final two combined sweet spot maps (Fig. 6). However, there are also some parts of the city with notable differences between the two approaches. One example area zoomed in Fig. 5 shows the McCaskey High School and Lincoln Middle School area being included as a sweet spot in the Even Weights instead of People's Choice scenario. The primary reason behind this difference was the lower weight assigned to the social vulnerability layer in the People's Choice than in the Even Weights scenario. When rated by the survey respondents, the social vulnerability weight became 0.157, lower than the 0.2 value in the Even Weights scenario. Therefore, although this location was indicated by the social vulnerability map as more vulnerable [Fig. 3(e)], the lower social vulnerability weight of 0.15 in the People's Choice scenario caused a reduction in its overall score, driving this location to be just below the sweet spots threshold.

Comparison of Sweet Spots with Existing GSI

The City of Lancaster has already implemented approximately 500 individual GSI features, including vegetated swales, tree trenches, filter strips, green roofs, infiltration bioretention basins, infiltration trenches, naturalized basins, permeable pavement, and infiltration surface beds. We compare existing GSI facilities to the areas with our designated sweet spots using both weighting schemes. Only 16.4% of GSI facilities are above the 90th percentile of locations using the equal weighting scheme and 16.6% using the People's Choice weights (Fig. 7). Perhaps Lancaster is prioritizing hydrologic function above all other objectives. However, when focusing exclusively on the hydrology layer, only 6% of existing GSI facilities are above the 90th percentile TWI. Therefore, there are likely gains to siting future GSI locations based either on hydrology or on a more holistic set of objectives (Fig. 7).

Discussion

The City of Lancaster, like many other urban areas around the world, has multiple stormwater-related concerns and intends to leverage GSI as a key solution (City of Lancaster 2011). Although GSI has the potential to provide numerous benefits, GSI siting approaches in many cities have often focused on solving stormwater or sewer outflow problems or opportunities to leverage other infrastructure projects and needs (City of Lancaster 2011; Green et al. 2021). To further GSI siting considerations based on additional functions provided by GSI and ensure equitable access to these



(a) (b)

Fig. 4. The two final combined maps where criteria layers were weighted (a) evenly; and (b) with survey results.

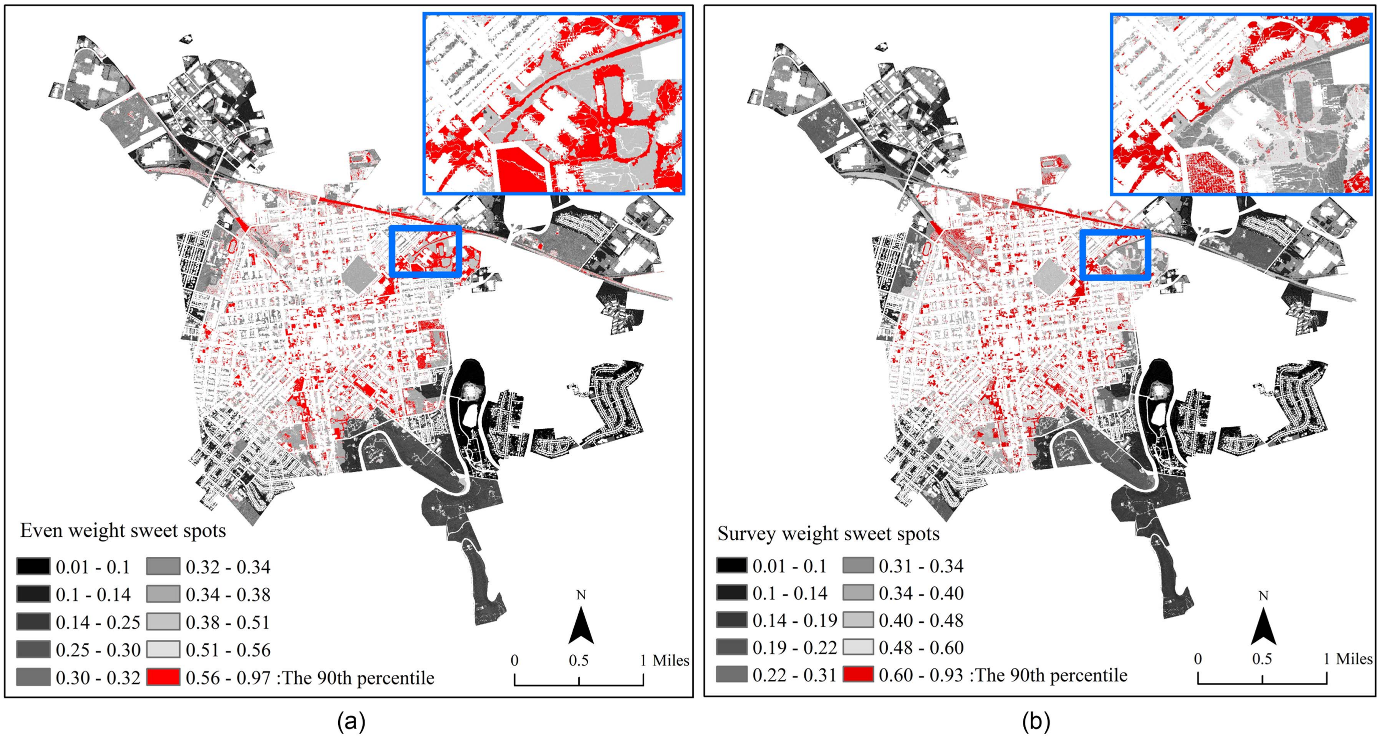


Fig. 5. Final combined maps with 90th percentile values highlighted in red as 'sweet spots' for potential GSI implementation under the (a) Even Weights; and (b) People's Choice scenario. In each, an example area in northeast Lancaster is highlighted to showcase cross-scenario differences in sweet spot designation.

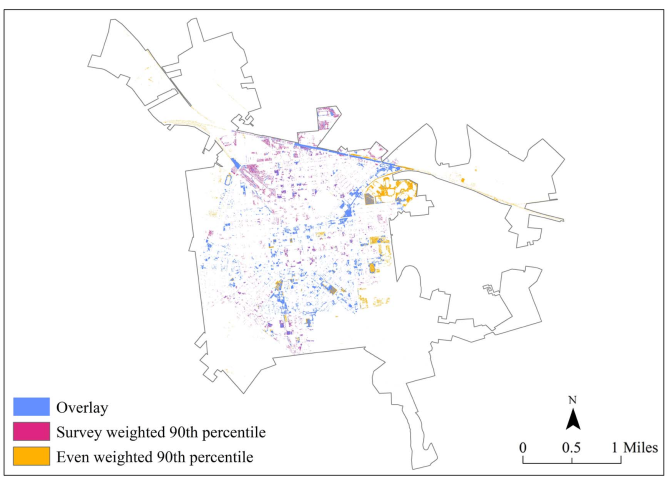


Fig. 6. Overlap of the two 90th-percentile sweet spot maps. Common pixels between two sweet spot maps are highlighted in blue.

benefits, we present a multicriteria spatial analysis approach to identifying sweet spots of GSI implementation through a case study in Lancaster. After weighing and combining five criteria layers with two approaches (even weighting versus People's Choice), we found a significant overlap (72%–74%) between the final two combined sweet spot maps. Only 16.4% of existing GSI in Lancaster are located in the evenly weighted criteria sweet spots, compared to 16.6% for the People's Choice sweet spots based on survey weights. We discuss the advantages, customization, and limitations of our method and the implications for GSI planning in the following sections.

Methodological Advantages

Our work adds to a rapidly growing collection of approaches for planners, designers, and decision makers to consider as they seek to improve GSI siting strategies. The most important advantages of our approach are its simplicity, broad data availability, and the incorporation of community preference through a choice experiment survey. Additionally, the method can be customized in various ways for other regions based on research or implementation goals, data availability, and computational capability.

First, selecting critical criteria with publicly available data is important for the method to be transferable. Most of the data we used, e.g., DEM, census, and land cover, is widely available in the United States. The weighted linear combination method also makes the aggregation of the layers highly computationally efficient, enabling rapid testing of multiple weighting scenarios.

Second, unlike most previous studies, our method integrates the perspectives of residents in analyzing GSI siting priorities. Historically, GSI siting approaches had generally focused on 'expert opinions' (e.g., Apud et al. 2020; Meerow and Newell 2017; Sarabi et al. 2022), while largely neglecting the values of community members (Meyer et al. 2018). In this work, we did incorporate expert views in consideration of included criteria, but we also explicitly integrated community preferences into the decision-making process. This is important because it is the residents who experience the day-to-day water challenges and interact the most closely with proposed solutions, and there is documented need for increased community engagement in the GSI planning process (Campbell-Arvai and Lindquist 2021).

It is worth noting that there is 72%–74% overlap between two layers when dividing the intersecting area by the 90th percentile of even weight and survey weight scenarios, respectively (i.e., almost three-quarters of either sweet spots layer is in common with the

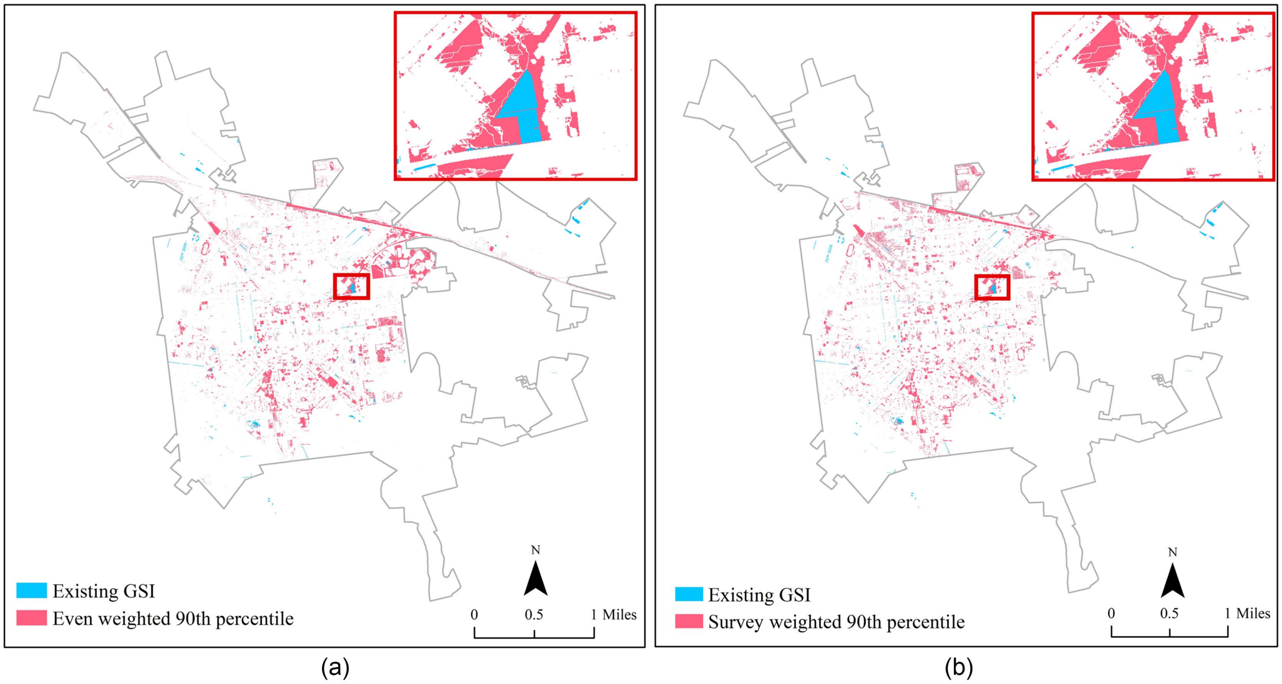


Fig. 7. Overlap of existing GSI with the 90th percentile sweet spots under the (a) Even Weights; and (b) People's Choice scenario.

other sweet spots layer). It is ideal to explicitly consider the community preferences and insights, and more than 25% of identified sweet spots were different in the 'People's Choice' layer. However, if there are not the resources to do a full choice experiment or similar quantitative evaluation of preferences, simply broadening the considered criteria is an important first step to improving GSI siting strategies.

Customization of the Method

Next, there are multiple ways in which our method can be customized for other regions. We briefly provide two examples regarding the selection of criteria (and associated metrics) and the spatial analysis of the sweet spots. While the five criteria we considered were initially determined based on discussions among the interdisciplinary project team in light of data availability, other criteria may be deemed important in other cities. For example, in cities trying to leverage vacant lots to create multifunctional green infrastructure, a vacant properties layer can be included. Additionally, alternative metrics can be considered for a given criterion. For example, for the hydrology layer widely recognized as a key GSI siting criterion, the specific metric deemed most appropriate could vary. The availability of certain spatial data can facilitate a more detailed hydrologic model to be employed beyond the TWI method we used. Additionally, if more detailed data was available on other constraints such as underground utilities or public right-of-way, this could be included to better refine the most feasible final locations.

Regarding the spatial analysis of the sweet spots, what constitutes a sweet spot can also be customized based on factors such as research objectives, planning goals, or budget constraints. Besides the weighted linear combination method we employed, others have used spatial analysis-based approaches such as clustering or hotspot analysis (e.g., Marks et al. 2022). In adapting our method, the key decisions, besides the selection of criteria layers discussed, are the weighting of layers and the threshold value for the sweet spot. The overall goal is to identify values at the 'undesirable' end of the value range in the final combined layer, i.e., the values most subject to flooding, with the highest proportion of impervious area and social vulnerability. What extent of values to include is somewhat of an arbitrary decision. For example, instead of using our selection of the 90th percentile values of the final weighted, combined layer, decisions can be grounded in financial and feasibility (e.g., parcel size) constraints to identify the extent of priority areas based on available budget for GSI installation. Additionally, one can choose to not isolate the 'sweet spots' and leave the final combined layer presented as a range of values clustered in some way (e.g., as quantiles), giving the local decision makers the flexibility to choose the number of priority sites (Meerow and Newell 2017).

Method Limitations and Opportunities

Despite the advantages and flexibility mentioned, we note several limitations and future considerations of our method. First, even with careful methodological considerations, the representativeness of the survey sample of the broader population cannot be assured due to the low response rate. Because the survey was administered during the early stage of the COVID-19 pandemic, the many other sources of stress in people's lives may have contributed to the lack of responses. As previously noted, the demographics of respondents are somewhat consistent with overall city demographics, but there are several potential biases noted, including age, race, income, and education. Thus, there may be some bias in the resulting weights (e.g. possible underrepresentation of social vulnerability). If possible, follow-up studies should be conducted to capture a larger number and a broader range of residents to verify the factor weightings of the current study.

Another issue requiring future investigation is to determine the appropriate scale of analysis. In our work, data with the highest available spatial resolution (e.g., census block groups versus tracts, highest resolution elevation, or land use data) were selected where possible to enhance the accuracy of criteria layers. For preparing the social vulnerability layer, we followed the SoVI method

(Cutter et al. 2003), but because we used block groups instead of census tracts as units for calculations, some of the data available for census tracts were not available at the block group level. Therefore, we had to eliminate some variables used for SoVI calculations and use the available data. As the unit of the analyses decreases, the variability generally decreases, which should lead to more realistic results. However, challenges result from uneven resolution across layers, where the highest spatial resolution of socioeconomic data is still much more coarse than land cover or topographic data. Aggregated socioeconomic data are also subject to the 'Modifiable Areal Unit Problem,' which is a source of statistical bias resulting when spatial data are aggregated into blocks or tracts; previous research evaluating overlap between social and flooding vulnerability has identified differences in priority areas for interventions based on the level of aggregation selected (Hinojos 2022).

Implications

Our mapping provides several interesting observations of current GSI patterns and practical implications for future GSI implementation in Lancaster. First, the result that a low percentage (6%) of existing GSI is located in hydrologic priority areas (i.e., with 90th percentile TWI values) suggests that many GSI facilities are already being implemented in locations for reasons other than simply maximizing flood mitigation. It should be noted, however, that this low amount of overlap may be due to considerations of the GSI type being implemented. GSI focused on detention and retention may be best implemented directly in the areas with the highest TWIs, where they can effectively capture accumulated stormwater. However, infiltration-focused GSI may function better when implemented just upslope of zones with the highest TWI, where there may be a greater depth to the water table. This demonstrates the opportunity to customize the chosen indicators based on precise GSI goals and to use the identified sweet spots as a starting point for identifying the exact future locations of GSI. Future iterations of GSI siting tools could be customized for different types of GSI.

Second, the observation that only 16% of existing GSI are located in identified sweet spots presents an opportunity to target future GSI implementation to sweet spots. This small overlap is understandable because, for identifying its demonstration projects, Lancaster used four prioritization criteria that are different from the five we mapped. They included runoff capture cost efficiency, integration with other infrastructure needs, external grant funding, and public acceptance and education (City of Lancaster 2011), and most of which are difficult to quantify and map with specific variables or metrics at the city scale. Given that recent scholarship has highlighted the common gaps between overarching planning goals and variables actually applied in GSI siting in many US cities (Hoover et al. 2021), it is a prime opportunity for the city to (re) evaluate how well existing GSI implementation matched initially proposed priorities and planning goals. Our mapping informs how historical criteria can be broadened to include other critical variables easily mapped at the city scale. Finally, the identified sweet spots can be used to inform future GSI locations. For example, the railway corridor at the northern edge of Lancaster, the several large industrial, commercial, and school parcels around New Holland Ave., and areas around West Chestnut St. appear to be promising locations identified by both weighing scenarios. City stormwater managers can examine the individual criteria layers for particular reasons behind the high combined values of these parcels, meanwhile factoring in additional considerations such as the four previously prioritized in the city's 2011 plan.

The utility of our method is that it can be replicated and customized for other regions. Our work adds to the toolbox that planners, designers, and decision makers could leverage as they seek to improve GSI siting strategies while working under various physical, social, and financial constraints. Future work can continue to improve the possible indicators, assess the function and benefits of GSI installed based on these optimization approaches, and identify opportunities to further improve implementation strategies. In particular, we need to strive to ensure that improvements for implementation strategies are being discussed as part of a transdisciplinary framework to bridge science and practice (Ramyar et al. 2021).

It is also important to note that GSI may not be considered a universal good. While there are many documented benefits, potential 'dis-services' can become significant barriers to implementation. These can include mosquito habitat, generation of pollen or pollutants such as volatile organic compounds, undesirable aesthetics (e.g., messiness or weediness) by community members, or 'green gentrification' (i.e., the inflation of nearby housing prices) (Meenar et al. 2022; Nassauer 1988; Pataki et al. 2011). Many of these issues can be managed with appropriate design decisions, such as types of vegetation, and adequate maintenance, but adequate policies have to be in place to prevent green gentrification. Finally, any GSI planning and design project must consider the broad range of services and potential dis-services to maximize the environmental, social, and economic benefits of GSI.

Conclusions

The City of Lancaster, Pennsylvania, like many aging cities elsewhere, has various stormwater-related challenges. The city has already started leveraging GSI as part of its stormwater management strategies. In this case study, we presented a relatively simple and customizable approach for considering multiple social, environmental, and logistical factors in identifying priority locations for GSI implementation. We compared two different approaches to weighting the chosen factors, one of which was based on surveyed community preferences. We believe this is an important improvement over previous approaches, as it better represents resident perspectives in the decision-making process.

By identifying sweet spots outside existing GSI areas, our approach highlights future implementation opportunities for the City of Lancaster, meanwhile offering broader implications for potential ways to improve future siting approaches. The presented approach will help stakeholders and organizations create a more comprehensive, objective, yet simple process for GSI siting that not only helps to address stormwater challenges, but also improves access of vulnerable residents to the benefits of GSI.

Data Availability Statement

All data, models, and code generated or used during the study appear in the published article.

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Supplemental Materials

There are supplemental materials associated with this paper online in the ASCE Library (www.ascelibrary.org).

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