Spatial Sustainability Assessment of Green Stormwater Infrastructure for Surface Transportation Planning, Phase III

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Final Report

by
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16. Abstract

Transportation authorities are responsible for managing the stormwater runoff that carries pollutants from the transportation-adjacent land and vehicles. The proper stormwater management approach like green infrastructure can help control flooding and the runoff pollutants that may impair water environment and threaten the ecosystem and human health. Furthermore, green infrastructure that can be applied at different spatial scales and decentralized arrangements, have been adopted and implemented in the transportation infrastructure design. However, such implementation is project-based without analysis at system level or sewer scale. A framework is needed to design and evaluate the integration of green stormwater infrastructure in transportations planning at systems level. The overall goal of the proposed project is to develop a modeling framework integrating hydrological simulation, water quality modeling, life cycle assessment (LCA) and cost analysis (LCCA) that can be used for design and planning for surface transportation with spatial implementation of green infrastructures. The phase III of the project developed a system-level optimization framework to determine the optimal allocation (i.e., location, size, and type) of GSI implementation, completed with the deliverables of a spatial optimization model, and a scenario analysis of runoff, water quality, environmental impacts, and cost of existing and optimized candidate GSI implementation.

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Abstract: Transportation authorities are responsible for managing the stormwater runoff that carries pollutants from the transportation-adjacent land and vehicles. The proper stormwater management approach like green infrastructure can help control flooding and the runoff pollutants that may impair water environment and threaten the ecosystem and human health. Furthermore, green infrastructure that can be applied at different spatial scales and decentralized arrangements, have been adopted and implemented in the transportation infrastructure design. However, such implementation is project-based without analysis at system level or sewer scale. A framework is needed to design and evaluate the integration of green stormwater infrastructure in transportations planning at systems level. The overall goal of the proposed project is to develop a modeling framework integrating hydrological simulation, water quality modeling, life cycle assessment (LCA) and cost analysis (LCCA) that can be used for design and planning for surface transportation with spatial implementation of green infrastructures. The phase III of the project developed a system-level optimization framework to determine the optimal allocation (i.e., location, size, and type) of GSI implementation, completed with the deliverables of a spatial optimization model, and a scenario analysis of runoff, water quality, environmental impacts, and cost of existing and optimized candidate GSI implementation.

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INTRODUCTION

During intense precipitation, the stormwater drainage system may reach its capacity quickly that can lead to urban flooding and influence the performance of the connected ground transportation system (e.g., reduced road capacity even road closure). This may cause significant deterioration of mobility and accessibility to sites where critical activities occur (e.g., health care services and schools). Besides, National Pollutant Discharge Elimination System (NPDES) regulates that transportation authorities are responsible for managing the stormwater runoff that carries pollutants from the land adjacent to road transportation systems. The proper stormwater management can help control flooding and the runoff pollutants that may impair water environment and threaten the ecosystem and human health. Green stormwater infrastructure (GSI) is a stormwater management approach with many economic and human health benefits including: flood mitigation, erosion control, improved water quality, groundwater recharge, mitigated effect of urban heat islands, reduced energy demands for cooling, and enhanced aesthetics and access to green space (Bowen and Lynch, 2017; Demuzere et al., 2014; Wendel et al., 2011). Unlike grey stormwater infrastructure systems that are often large and centralized, GSI can be designed at different spatial scales and implemented in decentralized arrangements (Suppakittpaisarn et al., 2017). GSI like basins (Belizario et al., 2016), bioswales (Lucas et al., 2015), bioretention (Lucke and Nichols 2015), and constructed wetlands (Li et al., 2016) have been adopted and implemented in the transportation infrastructure design. These technologies have proven effective in terms of reducing runoff and pollutant loads at the individual site or project level. However, implementation and analysis of GSI at system level or urban watershed scale is generally lacking. As Roy et al. (2008) pointed out that "sustainable urban stormwater management must be planned and implemented at the watershed scale," a framework is needed to design and evaluate the integration of GSI in transportations planning at system level. Such a framework can help understand the interaction of stormwater and transportation systems, the possible impact of stormwater runoff on the road network, the possible methods of mitigating the impacts and increasing resilience of both stormwater and transportation systems responding to disruptive events, and the environmental and economic benefits of sustainable stormwater management system with respect to runoff quantity and quality control.

The ***overall goal*** of the proposed project is to develop a modeling framework integrating hydrologic simulation, water quality modeling, life cycle assessment (LCA) and cost analysis (LCCA) that can be used for design and planning for surface transportation with the spatial implementation of GSI. It can model the effect of GSI on improving flooding and water quality, and assess their life cycle costs and environmental and health impacts. The objectives of the project include (1) developing a method for constructing an inventory of the implemented GSI using Tampa as a case study area; (2) integrating hydrologic modeling with water quality modeling for scenario analysis of GSI implementation at watershed scale; and (3) developing a spatial optimization model for GSI implementation based on the integrated LCA-LCCA-optimization framework. Corresponding to the set of objectives, the project is conducted in phases. The completed work in Phases I and II included two geographical information system (GIS) based methods, one for creating an inventory of existing GSI relevant to the road system according to GSI footprints and visual features, and another for determining the candidate GSI for future implementation with respect to GSI's location, size, and type, according to the terrain, land cover, land use, and the necessity of stormwater control. For the case study area in Tampa, FL, a GIS layer of existing GSI and a GIS database of candidate GSI were created, which can be overlaid with transportation and grey stormwater infrastructure network. In the reporting period, Phase III research is close to completion, which is working on the improvement of the hydrologic model and the development of an optimization framework. The trade-off between environmental, human health, and economic impacts is investigated for the optimal and other scenarios of GSI implementation.

Phase III Project

Phase III project aims to develop a system-level optimization framework to determine the optimal allocation (i.e., location, size, and type) of GSI implementation, completed with the deliverables of a spatial optimization model, and a scenario analysis of runoff, water quality, environmental impacts, and cost of existing and optimized candidate GSI implementation. Two major activities were performed in Phase III (Figure 1).

First, A MATLAB-based multi-objective optimization model using the binary genetic algorithm was established to identify the optimal allocation (i.e., location, size, and type) of GSI implementation. The optimization minimizes environmental, economic, and human health impacts at the system level associated with the construction, operation, and maintenance of GSI. For the case study of Tampa, the optimal solutions were found as a certain amount of candidate GSI selected with the information of location, size, and type.

Second, the evaluation of runoff, water quality, environmental impacts, and cost for the optimal scenarios were completed using LCA, LCCA, and a SWMM-based hydrological model. Some discussion was made for future GSI planning according to the results of scenario analysis.

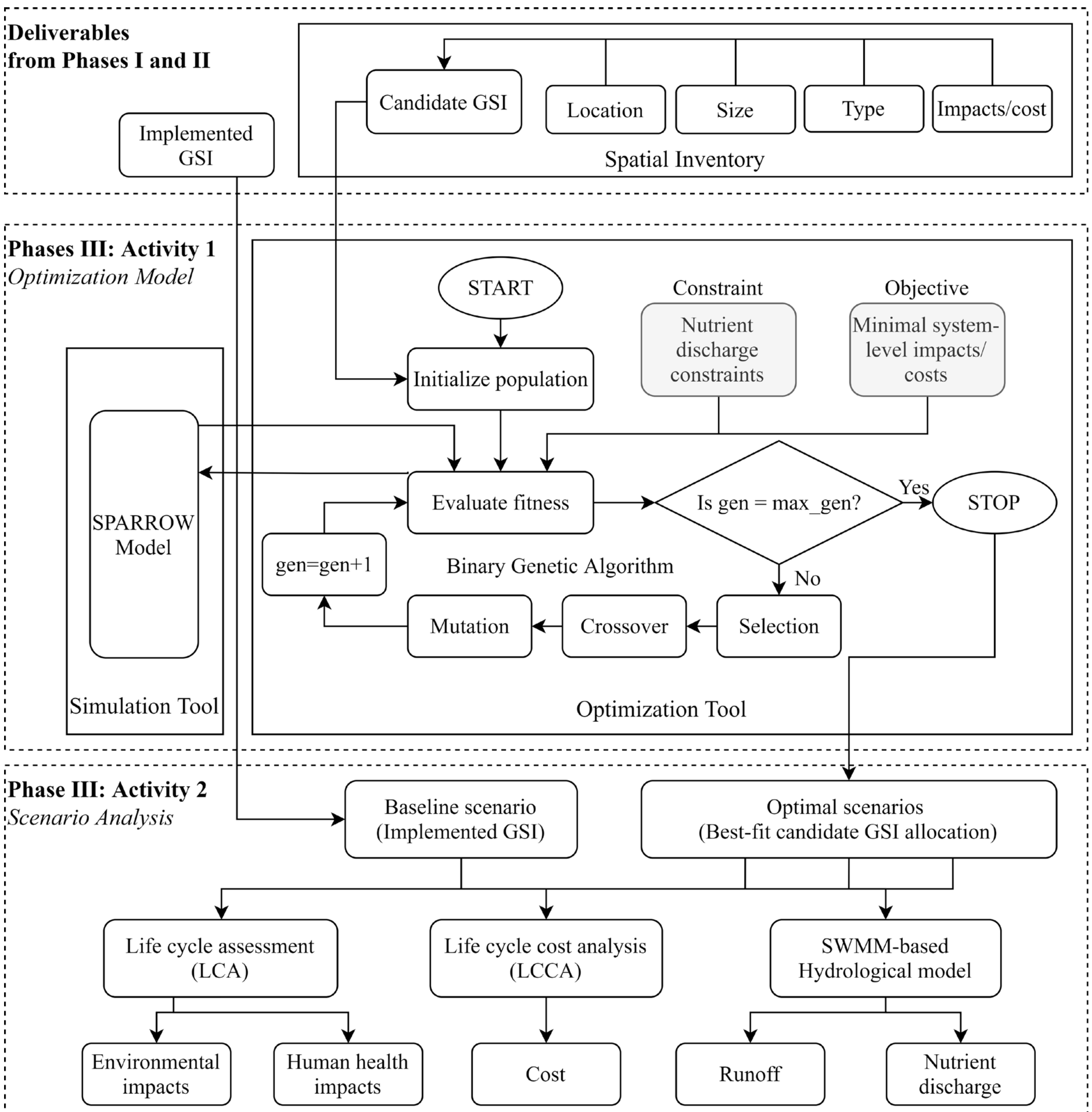


Figure 1. The process diagram in Phase III research.

METHODOLOGY

Methodology Development

The Phase III research were conducted into two major activities, including the development of an optimization model and an analysis of the generated optimal scenarios (Figure 1).

The spatial optimization in this project includes three major components, i.e., a spatial inventory, a simulation tool, and an optimization tool (Figure 1).

The spatial inventory refers to the database of candidate GSI that was created in Phase II research. A certain amount of candidate GSI were identified with location, size, and type. Three alternative GSI types were assigned to each candidate, including bioretention systems, vegetated filter strips, and wet/dry ponds. For each GSI type, the same technology configuration is adopted but the surface size at each location varies according to the drainage areas and infiltration rate. Based on the GSI's type, configuration, surface size, and drainage area, the life cycle environmental impacts and costs were estimated for each GSI. The information about location, size, type, environmental impacts, and costs was saved together with each candidate GSI data point to create a GSI database. This database feeds into the optimization algorithm as the initial population. In addition to the candidate GSI, a framework was developed for creating an inventory of the implemented GSI that serves as the baseline of the GSI implementation.

A simulation tool is needed to evaluate the system-level nitrogen discharges as the performance for each iteration in the optimization. SPARROW model (SPAtially-Referenced Regression On Watershed Attributes model; Preston & Brakebill, 1999) was selected as the simulation tool since the computation is less intensive as a statistical model and the calibrated model is available for the study area.

Then, a multi-objective optimization model was developed to identify the optimal allocation (i.e., location, size, and type) of GSI implementation. The optimization minimized environmental, economic, and human health impacts at the system level associated with the construction, operation, and maintenance of GSI. The nutrient discharge to Tampa Bay was set as the constraint. The binary genetic algorithm (GA) was applied and implemented in MATLAB for optimization. All the binary GSI options lined up like a chain, i.e., the population for GA. With the help of the processes of selection, crossover, and mutation, the best fits (so-called optimal solutions) were found as a certain amount of candidate GSI selected and each comes with the set of location, size, and type.

Eventually, the generated optimal scenarios were evaluated in terms of runoff, water quality, environmental impacts, and cost at the system level (i.e., the city scale). The environmental and economic impacts of the selected candidate GSI were estimated according to the LCA and LCCA results of individual GSI implementation. The city-scale runoff simulation with respect to candidate GSI implementation requires a fine-scale hydrological model. This research built and calibrated the SWMM hydrologic model to track the quantity and quality of surface runoff and to simulate the effectiveness of GSI in terms of runoff control based on past drainage delineation, elevation, land use, land cover, and the road network.

Data Collection

Table 1 summarizes the data collected for both the development of an optimization model and the analysis of the generated optimal scenarios. The deliverables of existing and candidate GSI datasets from Phases I and II research were adopted (Figures 2 and 3). All the GIS data of road system and stormwater management facilities were formatted as shapefiles and available to the public with the open data link. The reported street flooding provided by City of Tampa Transportation & Stormwater Services recorded the flooding locations during 2015-2017. The land use of Hillsborough County and population data by the U.S. Census Bureau were acquired in the year of 2018. The raster image of Digital Elevation Models (DEM) by USGS has horizontal resolution of 1m by 1m and vertical of 0.05m. The Watershed Boundary Dataset by USGS defines the national hydrological boundary at six different geographical levels from regions to sub-watersheds. The non-public raster image of Tampa land cover was created with a rule-based object-orientated classification method utilizing high-resolution imagery, LIDAR data and ancillary GIS data by USF Water Institute. It has a 1-foot-by-1-foot resolution, providing extremely high accuracy as a reference map. All the data were adjusted to the GCS_North_American_1983 geographic coordinate system, or the NAD_1983_StatePlane_Florida_West_FIPS_0902_Feet projected coordinate system when measurement was needed.

Table 1. The data used in Phase III research.

Dataset	Source
Existing GSI inventory	Phase I research (Xu et al., 2020)
Candidate GSI database	Phase II research
Reported flooding spots	Tampa Transportation & Stormwater Services
Watershed Boundary Dataset (WBD)	U.S. Geological Survey (USGS)
Digital Elevation Models (DEM)	
Population (2018)	U.S. Census Bureau
Land Use of Hillsborough County (2018)	Plan Hillsborough http://www.planhillsborough.org/gis-maps-data-files/
Tampa land cover	USF Water Institute
Road centerline	City of Tampa GeoHub http://city-tampa.opendata.arcgis.com/ Hillsborough County Public Works Department
Stormwater inlets	
Stormwater basins	
Stormwater discharge points	
Stormwater detention areas	
Stormwater gravity mains	
Stormwater pressured mains	
Stormwater open drains	

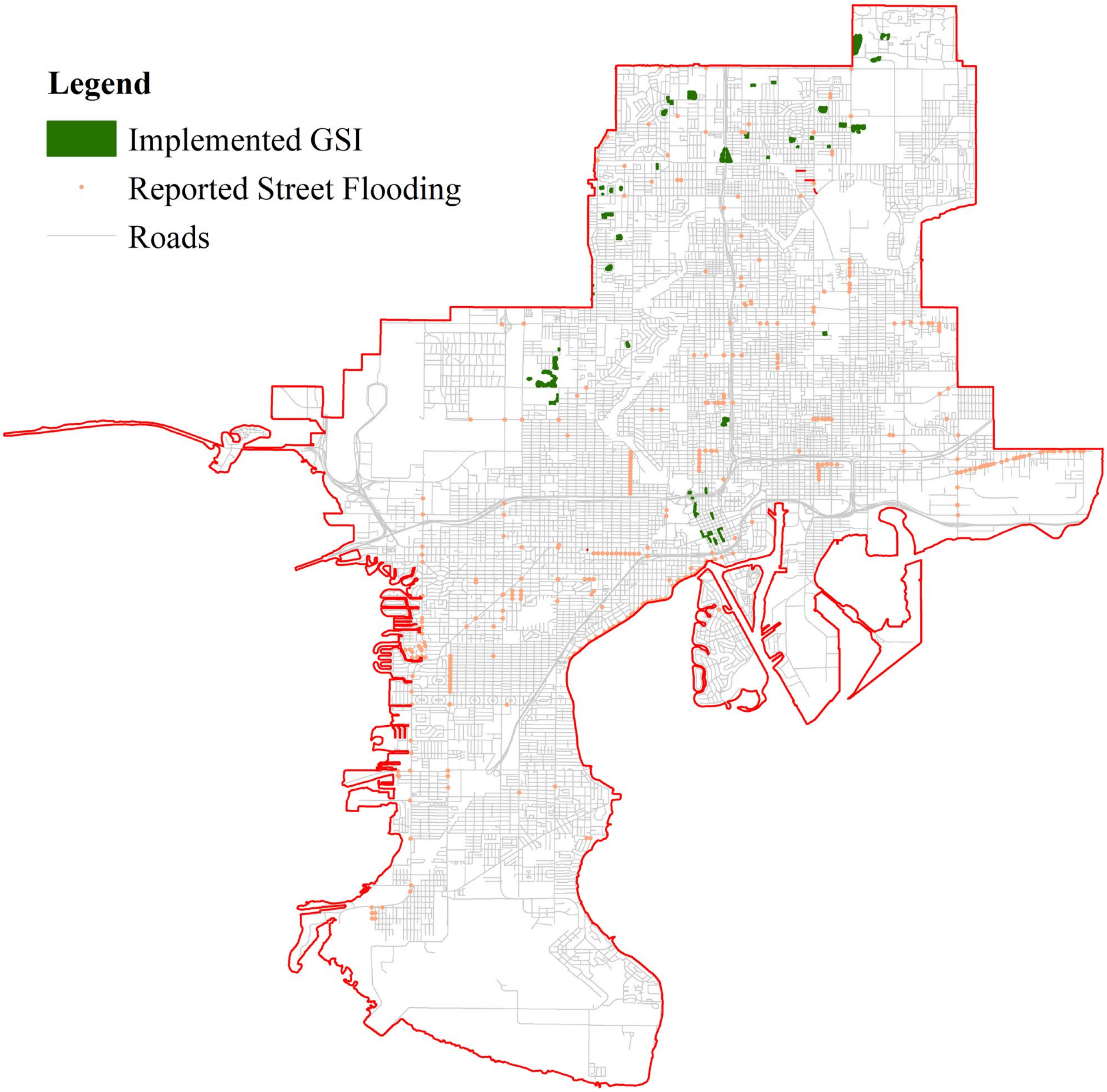


Figure 2. The study area and implemented GSI detected (from Phase I) in this research.

Study Area

The study area for the spatial optimization of nutrient management technology implementation should be:

1. a region under flood risk;
2. an area consisted of diverse land uses;
3. an area has high population density, but few existing GSI; and
4. an area could work as input to other hydrologic models.

The research selected the City of Tampa as the study area, excluding the New Tampa Area and the Tampa International Airport region (Figure 2). Most of the study area is covered by the Middle Hillsborough River-Spillway 20 subwatershed area (HUC12 code: 031002050503). Figure 2 also shows the reported street flooding provided by the City of Tampa Transportation and Stormwater Services recording the flooding locations from 2015 to 2017.

Spatial Nutrient-Loading Evaluation Model

This project adopts SPARROW, short of SPAtially-Referenced Regression On Watershed Attributes, as the spatial nutrient-loading evaluation model. SPARROW is a modeling tool for the regional interpretation of water-quality monitoring data developed by USGS, which is linked to a network of monitoring stations (Preston & Brakebill, 1999). The model is statistically calibrated, using equations expressed in terms of watershed flow paths (a network of stream reaches) and attributes. It uses watershed data and simple mechanistic features to statistically estimate the origin and fate of contaminants. SPARROW can estimate water quality conditions at both national and regional levels, addressing two major limitations of monitoring, including cost and geographic sampling bias. It can identify pollution sources including N by linking water quality conditions in each stream reach to

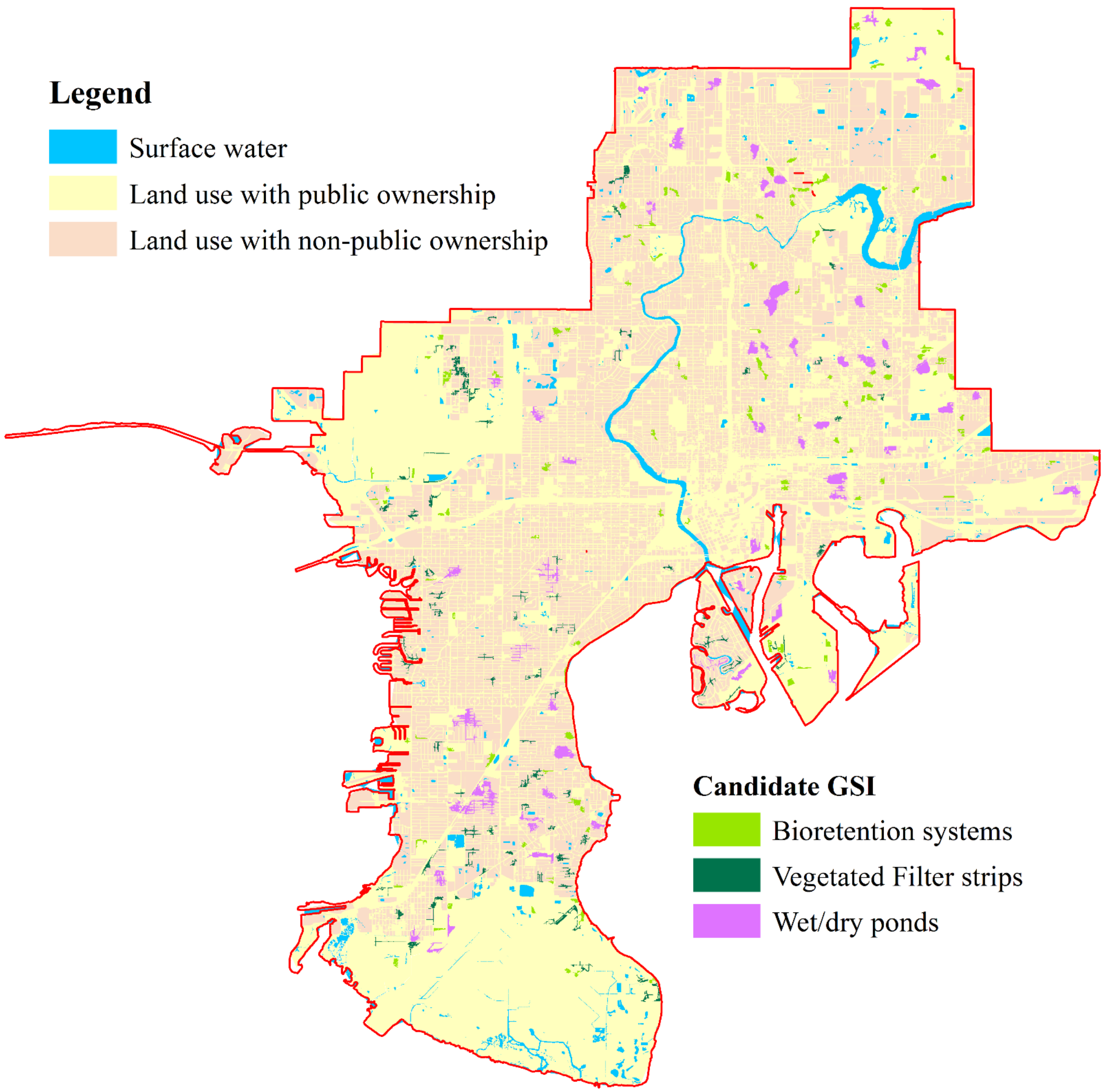


Figure 3. The candidate GSI identified in Phase II research.

individual sources in each upstream reach. It has the capability of uncertainty analysis for monitoring design.

The SPARROW model used in the spatial optimization was modified and calibrated for the nitrogen loading to the Tampa Bay area by Shih (2018). The SPARROW scripts can run on the platform of SAS, requiring about 20-min computing time for a single iteration.

Optimization Model

This project developed a multi-objective optimization model for GSI implementation in terms of nutrient management. The optimization model was used to determine the implementation of the GSI, i.e., location, type, and surface size and drainage area. The model minimized the total weighted environmental impacts and life cycle costs associated with the construction, operation, and maintenance phases to capture the environmental, human health, and economic impacts of the system design. The optimization model was coded in MATLAB with the genetic algorithm (GA) optimizer.

Objective Functions

The proposed mathematical formulation consisted of two objective functions. The first objective function (Equation 1) minimized the total weighted environmental impacts associated with GSI's installation and operation, based on the impacts of eutrophication (EU), global warming potential (GWP), and ecotoxicity (ET) normalized by GSI surface area.

$$\text{Minimize } Z_{impact} = \sum_{k}\sum_{t}(w_{EU}EU_t + w_{GWP}GWP_t + w_{ET}ET_t)p_{kt}DA_k \qquad (1)$$

Weighting factors were added to each impact category in order to obtain the total weighted environmental impacts; specifically, the weighting factors were acquired from Gloria et al. (2007) and the values for w_{EU}, w_{GWP}, and w_{ET} are 0.072, 0.084, and 0.349, respectively. The weighting scheme was judged by voting interest from stakeholders like producers, users, and LCA experts at three different time horizons (i.e., short term as 24%, medium term as 31%, and long term as 45%; Gloria et al., 2007). This objective function also considered the contribution of drainage area (DA). A binary option for each GSI (p_{kt}) was added in the function to determine whether the GSI facility is selected or not.

The second objective function (Equation 2) minimized the total costs including the life cycle cost (LCC), land use cost (LU), expressed as the slope of cost over GSI surface area, and the credits from the saving cost of nitrogen treatment (SN) by GSI, expressed as the slope of cost over GSI drainage area.

$$\text{Minimize } Z_{cost}=\sum_{k}\sum_{t} LCC_{kt}p_{kt}DA_{k}+\sum_{k} LU_{k}p_{kt}DA_{k} - \sum_{k}\sum_{t} SN_{kt}NP_{kt}p_{kt}DA_{k} \quad (2)$$

The definition of each parameter can be found in Table 1.

Table 1. The nomenclature in the spatial optimization.

Nomenclature	Description
Set	
k	Set of candidate sites for GSI
t	Set of types of GSI
Parameter	
DA_k	drainage area of GSI at location k
Imp_k	Impervious percentage according to land use at location k
Inf_k	Infiltration rate according to land cover at location k
w	Weight of impact categories to total impact
LCC_kt	Cost rate of construction of a GSI over surface area with type t at location k
LU_k	Cost rate of land use over surface area at location k
SN_kt	Credit rate of saving cost from nitrogen treatment by GSI over drainage area with type t compared to WWTP at location k
NP_kt	Removal rate of nitrogen by GSI with type t at location k
n_kt	Life time of a GSI facility with type t at location k
Variable	
p_kt	A zero/one variable that equals 1 if GSI implemented with type t at location k is selected, 0 otherwise

Optimization Algorithm

Each GSI was assigned with its location, size, type, environmental impacts, and cost, and each GSI works as a binary option, selected or not. All the binary GSI options initialized the population for GA, like a DNA chain. The length of the DNA chain is the amount of potential GSI. For each generation, some GSI are selected (marked as 1 in the DNA chain) and some are not (marked as 0). Some rules (i.e., selection, crossover, and mutation) help GA to produce the next generation. At each iteration, the GA selects individual GSI options (like a partial DNA chain) at random from the population to be parents and uses them to produce the children (a combination of partial DNA chains from parents) for the next generation. That is the process of selection and crossover. This optimization algorithm chooses the current and previous chains as parents, and uses single-point crossover that randomly picks a point on both parents' GSI chains. The portion on the right of that point is swapped between the two parent DNA chains. This results in two offspring, each carrying some genetic information from both parents. The two children chains will then be evaluated in terms of the fitness at individual iteration and the one with higher fitness will survive to produce the next generation. In addition, the rule of mutation applies random changes in the next generation. In the algorithm, a random number less than 10 of any GSI options were switched either from 0 to 1 or from 1 to 0 after the selection and crossover at each iteration. Each generation is simulated using the SPARROW model to evaluate its fitness until the given iterations are completed and the best fit is found. The Twain Shall Meet tool (Shvorob, 2020) was used as the data exchanger between SAS (the SPARROW's platform) and MATLAB (the optimization's platform).

In the fitness evaluation, the nutrient discharge to Tampa Bay at each generation is modeled and compared to the constraint; the generation fails if the nutrient discharge exceeds the constraint. For those generations that pass the constraint, the life cycle costs and weighted environmental impacts are used for fitness evaluation. Finally, an optimal allocation (or best fit) of existing and candidate GSI implementation is found from the spatial optimization model.

The multi-objective optimization was fulfilled using the solver gamultiobj function from the Global Optimization Toolbox in MATLAB. The gamultiobj function is designed to find the Pareto front (i.e., a set of points in the space of decision variables that have noninferior fitness function values) using GA. The gamultiobj solver can return the final population and its scores (objective values) with the inputs of the fitness function, the number of variables, and the bound constraints. The fitness function was set to kur_multiobjective.m function that computes two objectives (MathWorks, 2007). Table 2 lists the inputs and their values used in the optimization function.

Table 2. Inputs used in the optimization function in MATLAB.

Input	Description	Value
fitnessfcn	Fitness functions	kur_multiobjective
nvars	Number of design variables	3
A	A matrix for linear inequality constraints	ones(1,268)
b	b vector for linear inequality constraints	1
nonlcon	Nonlinear constraint function	Output from SPARROW
solver	Optimization solver	'gamultiobj'
options	Options created using optimoptions	MaxGenerations=500

Scenario Analysis

The analysis of runoff, water quality, environmental impacts, and cost for the optimal scenarios were completed using LCA, LCCA, and a SWMM-based hydrological model.

Environmental and Economic Impacts

Life cycle assessment (LCA) was used to evaluate the environmental impacts of the implemented and candidate GSI. The LCA in this project follows the ISO 14044 (2006) standard, containing four primary steps: goal and scope definition, inventory analysis, impact assessment, and interpretation. In terms of the life cycle of a full-scale GSI, the construction and operation and maintenance (O&M) stages were considered within the system boundary, including the processes of manufacturing, transportation, installation, and maintenance. The design for each type, i.e., bioretention systems, vegetated filter strips, and dry ponds, follows the best water quality performance configuration in the work of Xu and Zhang (2019), Hunt et al. (2009), and Shammaa et al. (2002), respectively, which guides the development of the life cycle inventory for each type. The lifetime of a bioretention system was assumed to be 15 years, vegetated filter strips be 20 years, and dry ponds be 30 years.

The LCA was conducted with the SimaPro PhD software (version 8.0) by PRé Consultants. The Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) version 2.1 by the USEPA was used for the assessment. The impact categories analyzed include eutrophication, ecotoxicity, and global warming potential.

Each GSI was calculated and assigned with the impact values of eutrophication, ecotoxicity, and global warming potential, based on its surface area using the regression model. Eventually, the environmental impacts were normalized with respect to the function unit (FU) of 1 kg TN removed, since the study targeted on nitrogen as the primary nutrient responsible for eutrophication in coastal areas (Howarth & Marino 2006).

The life cycle cost (LCC) in this project, included the capital cost, routine maintenance cost, corrective maintenance cost, and the electricity cost involved in the construction and maintenance. The LCC as net present value (NPV) was calculated by discounting all the costs mentioned above to present values. The discount rate was assumed to be 5%. Similarly, the regression model was developed to estimate LCC based on the GSI surface area. Each GSI was calculated and assigned with the LCC calculated using the regression model and GSI's surface area.

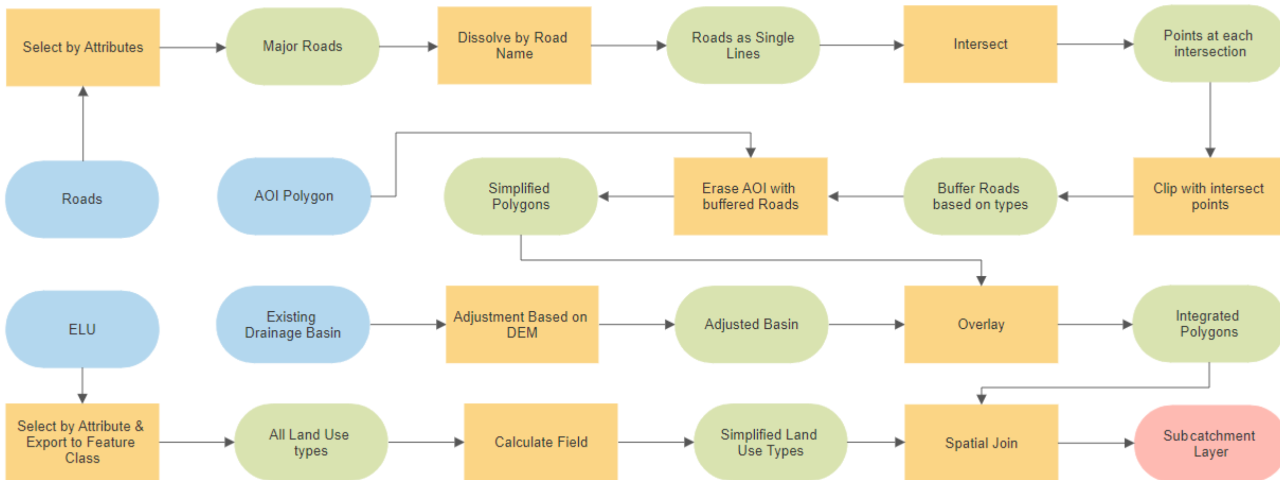
Runoff Control

In this project, the EPA SWMM model is selected for hydrologic runoff simulation. SWMM can track the quantity and quality of surface runoff during precipitation and is suitable for large study area modeling and simulation. SWMM categorizes most of the physical objects in the model into three groups: subcatchments (polygons), nodes (points), and links (lines). Subcatchments refer to physical areas of land, with data such as land use and slope being factored into the model. Nodes can be representative of a number of stormwater infrastructures such as inlets, discharge points, and storage units. Links are used to represent things such as pipes, open channels, and weirs. Other parameters such as temperature and evaporation rates are entered into the model separately from the physical objects.

Subcatchments in the model were delineated based on the land use data, road network, digital elevation (DEM), and existing stormwater basins. The processes using ArcGIS geoprocessing tools are summarized in Figure 4a with the input values from Tables 3 and 4.

Table 3. The inputs and values for the geoprocessing tools used for subcatchment simplification process.

Geoprocessing tool	Inputs and values
Select by Attribute	Field: ROADCLASS Attribute: Local
Dissolve	Field: FULLNAME Uncheck "Create multipart features"
Intersect	Output Type: POINT
Clip	Input: Dissolved Roads Clip Feature: Intersect Points
Erase	Input Feature: AOI Erase Feature: Buffered Roads
Buffer	Buffer Roads based on values in Table 3
Select by Attribute	Fields: Not Classified & Public
Spatial Join	Target: Integrated Polygons Join: HC Existing Land Use Join One-to-One Check Keep all Target Features Merge Rule for LU Type: Mode



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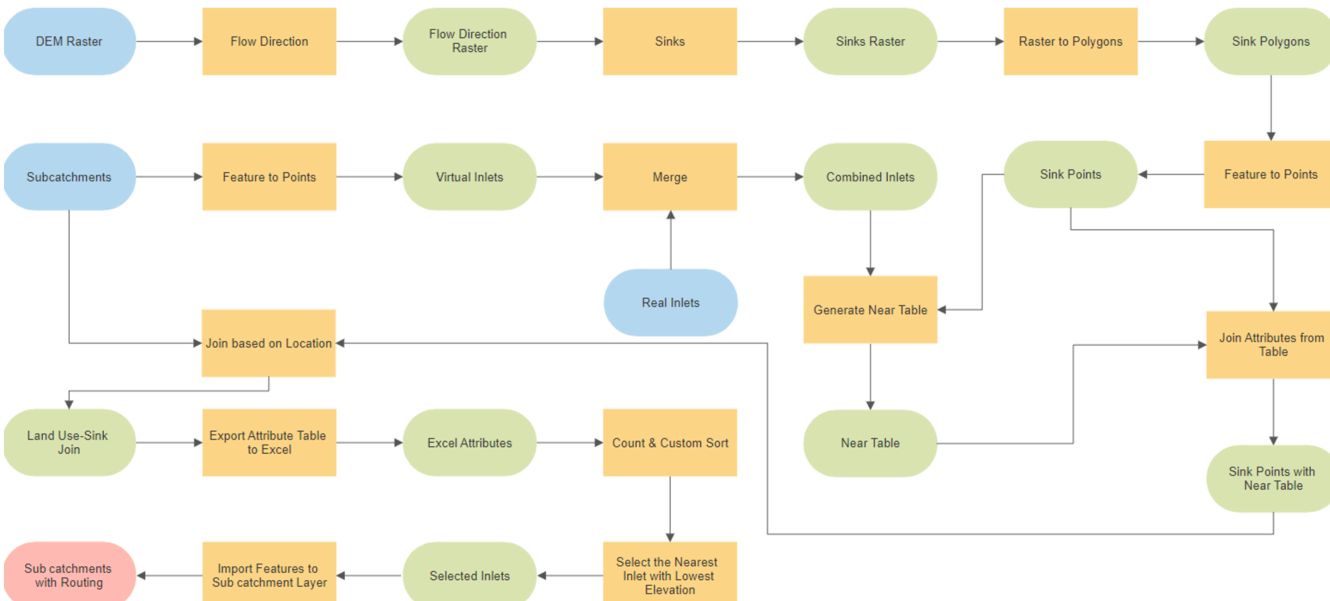

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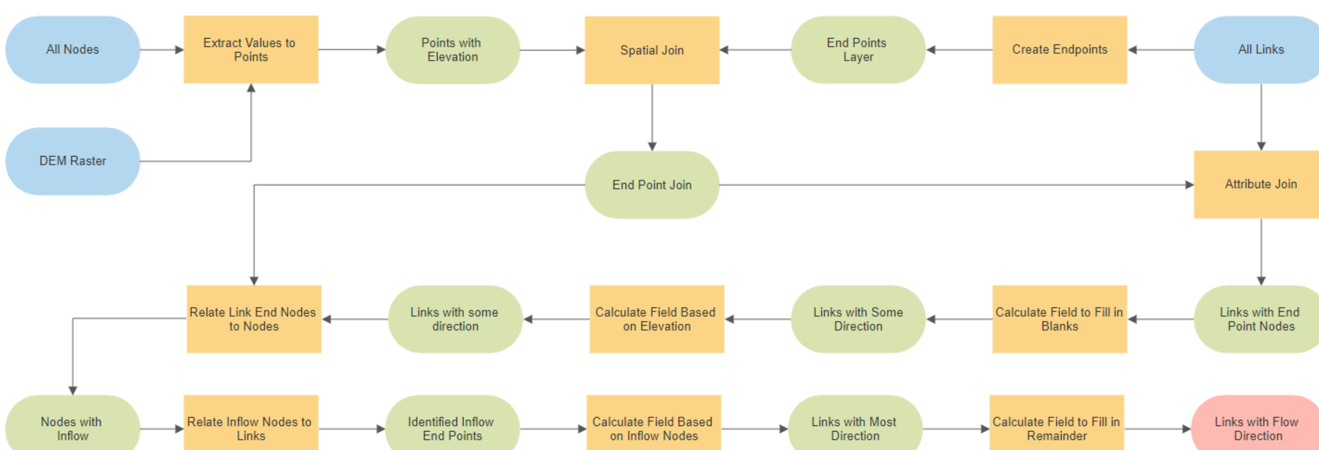

(c)

Figure 4. The subcatchment delineation process (a), The determination process of subcatchment routing (b), and the determination process of flow direction in the links used in the SWMM model development.

Table 4. Road buffer criterion.

Road type	Lanes	Shoul-der/bike	Buffered width/ft	Total width/ft
Local	1/side	4	16	32
Freeway	2/side		28	56
Collector	2/side	6	30	60
Minor arterial	2/side	6+6	36	72
Neighborhood collector	1/side	4	16	32
Principal arterial	3/side		54	108
Ramp	1/side		14	28
Right of way	Max 50ft width		25	50

The parameters of each subcatchment such as slope, impervious rate, area and width can be calculated and joined to the attribute table in ArcMap. As for other infiltration parameters, the values were obtained based on SWMM User Manual. The details are summarized in Table 5.

Table 5. The parameters for each subcatchment.

Parameter	Values and Methods
Rain Gage	Multi-rain gages
Area	Calculate Area Tool in ArcGIS
Characteristic Width	Calculate Field: 4*area/perimeter
% Slope	Slope tool with DEM raster; average slope for each polygon (subcatchment)
% Impervious	Calculate Field based on assumed values
Mannings Number for impervious/pervious area	Assume based on SWMM User Manual
Depth of depression storage for impervious/pervious area	0.05 in/ 0.1 in
% of impervious area with no depression storage	Use default value of 25%
Subarea routing	Outlet
Infiltration	Green Ampt
Snow Pack	None

Nodes are one of the major objects in SWMM. In this project, junctions (inlets, all points at intersection), outfalls (discharge points), and storage units (detention/retention ponds) nodes were considered. For junctions, all points were merged into one layer and given a unique name. The same process did for outfalls and storage units. The determination process of surface runoff routing for each subcatchment is summarized in Figure 4b. The main required parameters for junctions and outfalls are invert elevation, which is the bottom elevation of the structure. Most of the points in the dataset do not have information for invert elevation. For those points, the elevation of the ground at each point was extracted as an attribute using the Extract by Points tool and the invert elevation was determined by subtracting the distance to ground value from the elevation of each point.

For the storage units, some of the detention ponds have their name in the attribute table which can be searched online to find their basic information. For those that do not have information, an average value was selected according to the SWMM User Manual. Besides, both Initial Depth and Surcharge Depth were assumed to be 0. Initial Depth was set to be 0 assuming that there was no significant rainfall before the simulations. The surcharge depth is a parameter representing the additional depth a junction can fill up before it floods, which is used to simulate manholes or pressurized mains. This was assumed to be 0 to investigate the effect of green infrastructures on runoff control.

Links in the model are used to represent pipes and channels that carry the stormwater from node to node. Therefore, the most important parameters of Links are the nodes they are connecting. Some of the links in the dataset contain the information. For the links that do not have the information, the process in Figure 4c was used to help determine the flow direction in the links.

After all the parameters been calculated and joined in ArcGIS, the information was saved as shapefiles. A R package named ‘swmmr’ was used to rewrite the data in the shapefiles into SWMM input file.

OPTIMAL SCENARIO GENERATION AND ANALYSIS

Best-fit Solutions from Five Trials

The optimization model is set to run 500 iterations for every trial. Five trials were conducted and five different optimal solutions were found (marked as Opt 1 to Opt 5). GA is designed to search the solution with the best fitness and that is why the best-fit solutions in each trial were different from each other. Figure 5 shows the optimal solution of GSI allocation in Trial 1 (Opt 1).

Statistical Analysis

For all the five trials, the selected candidate GSI are relatively evenly distributed within the study area. Table 6 summarized the amount of GSI of different types in each optimal solution. The total amounts of GSI are almost the same for all the five solutions, varying from 50 to 52. The similarity of the total GSI amount in optimal solutions may be due to the minimization of total costs. The selection of a certain GSI type has larger variation, i.e., 12 to 19 for bioretention systems, 25 to 34 for vegetated filter strips, and 5 to 9 for dry ponds. Opt 1 selected most bioretention systems (19 counts) but fewer dry ponds (6 counts), while Opt 2 selected most dry ponds (9

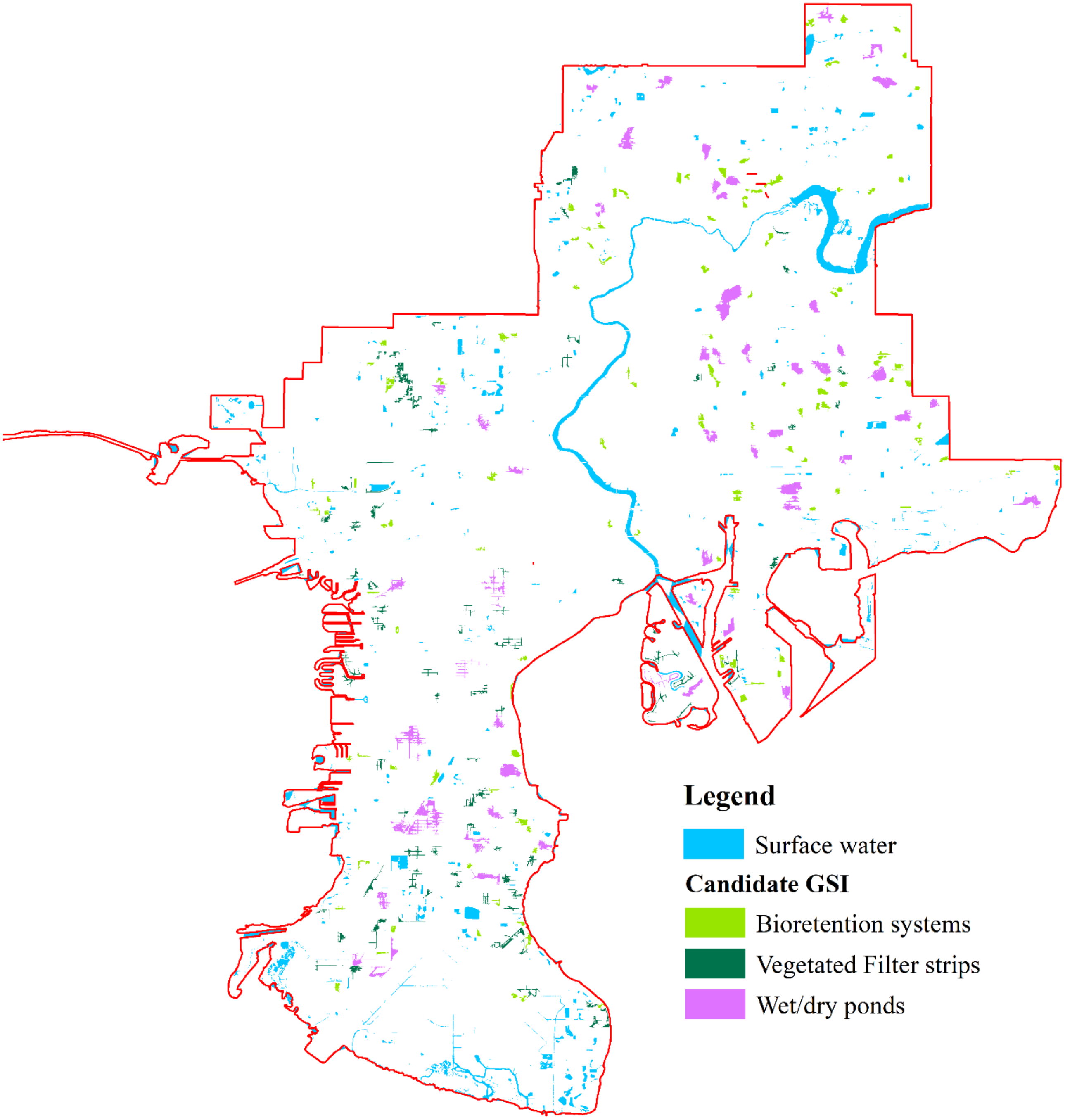

Figure 5. The optimal solution of green stormwater infrastructure (GSI) allocation in Opt 1.

counts) but fewer bioretention systems (14 counts). Although the amount of bioretention systems in the database is higher than vegetated filter strips (156 vs. 129), vegetated filter strips were selected more in the optimal solutions than bioretention systems. The reason may be that the bioretention system has an additional internal water storage zone (IWSZ) that requires more input on installation and maintenance, and makes it more expensive than the vegetated filter strip for the same surface size ($103.1/ft^2 for the bioretention system vs. $87.2/ft^2 for the vegetated filter strips).

Table 6. The amount of GSI in each optimal solution.

GSI type	Database	Optimal solution Opt 1	Opt 2	Opt 3	Opt 4	Opt 5	Average
Bioretention system	156	19	14	13	12	17	15
Vegetated filter strip	129	25	29	34	31	27	29.2
Dry pond	83	6	9	5	8	6	6.8
Total	368	50	52	52	51	50	51

Table 7. The average drainage area of green stormwater infrastructure (GSI) in each optimal solution.

GSI Type	Database (1000 ft^2)	Optimal solution (1000 ft^2)					
		Opt 1	Opt 2	Opt 3	Opt 4	Opt 5	Average
Bioretention system	143.8	257.4	274.1	278.2	280.4	267.5	271.52
Vegetated filter strip	150.3	187.5	167.8	161.7	166.3	178.4	172.34
Dry pond	601.3	873.4	842.2	914.1	856.1	871.9	871.54
Total Area	91729.4	14818.5	16283.4	13684.9	15368.9	14595.7	14950.28

Table 7 introduces the average drainage area of the selected GSI in each optimal solution. The average drainage area of each type has relatively low variation across all the five solutions. However, the total area for each solution has a larger variation from each other, as low as 13.6 million ft^2 in Opt 3 and as high as 16.2 million ft^2 in Opt 2. It is basically because of the amount of dry ponds selected in each solution since dry ponds have much larger drainage areas (average as 0.87 million ft^2) than the other two types. Though the average drainage area of bioretention systems and vegetated filter strips are similar in the database, the bioretention systems selected in the optimal solutions are much larger than vegetated filter strips (averagely 271.52 vs. 172.34 thousand ft^2). Bioretention systems have better nitrogen removal performance due to the additional IWSZ and contribute more to the reduction of environmental impacts. It means that the larger bioretention systems (i.e., larger surface area) are preferred that might be attributed to their high cost-effectiveness on impact reduction (about \$7.9 per point of weighted impact reduced for bioretention systems, \$8.2/point for vegetated filter strips, \$10.1/point for dry ponds).

Environmental and Economic Impacts

The weighted normalized environmental impacts of each optimal solution are calculated with the unit of millionpoints (a dimensionless unit for weighted impacts; Gloria et al., 2007) in Figure 6.

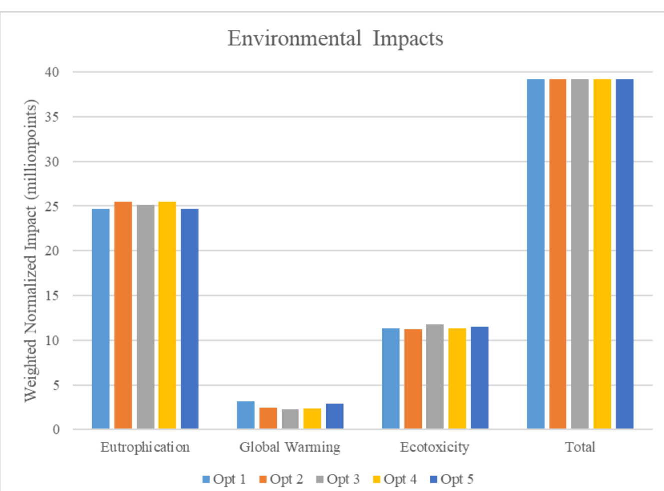

Figure 6. The weighted normalized environmental impacts of each optimal solution.

In Figure 6, eutrophication has the highest weighted impact followed by ecotoxicity. There is a minor difference between the five optimal solutions in each impact category but all the five solutions achieved the same total impacts.

Figure 7 summarized the annualized net present values of each optimal solution. The life cycle cost of the GSI facilities is the major contributor to the total cost. The credits saved from the nitrogen treatment by GSI contributed about 4% deduction to the total cost. Similar to the results of weighted environmental impacts, there is a minor difference between the five optimal solutions in each cost category but all the five solutions achieved the same total costs.

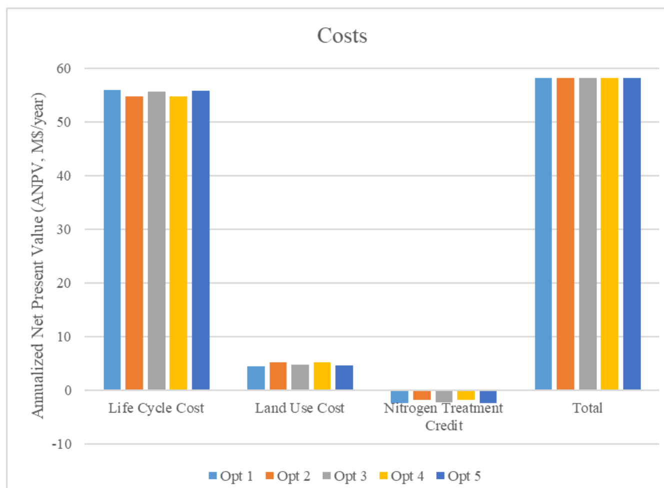

Figure 7. The annualized net present values (ANPV) of each optimal solution.

GSI Distribution in the Optimal Solutions

Kolmogorov–Smirnov test (K-S test) was used to examine whether the GSI distribution in the optimal solutions follows any pattern or not. One-sample K-S test examines the goodness of fit of a given set of data to a theoretical distribution (Berger & Zhou, 2014). Each optimal trial was tested, and the distribution of the distances between each GSI and its closest GSI was compared with normal distribution as the reference. If the GSI distances follow the normal distribution, it means GSIs in the optimal solutions are distributed randomly, and there is no specific distribution pattern for the optimal GSI allocation.

The data points of the distances between each GSI and its closest neighbor in the optimal solutions can be exported from

ArcGIS to Excel using the geoprocessing tool. Then the data points are examined using the ks.test function in R. The outputs from R include D value (Kolmogorov–Smirnov statistic) and p value. Each optimal solution's outputs are summarized in Table 8.

Table 8. The Kolmogorov–Smirnov test results for each optimal solution.

Optimal solution	D	p	Random distribution ($p < 0.05$)?
Opt 1	0.347	0.742	No
Opt 2	0.271	0.651	No
Opt 3	0.198	0.629	No
Opt 4	0.331	0.683	No
Opt 5	0.284	0.675	No

According to the K-S test results in Table 8, all the five optimal solutions do not follow a random distribution, indicating there is a certain distribution pattern of GSIs in the optimal solutions.

A series of two-sample K-S tests were also used to examine whether the different optimal solutions follow the same type of distribution. Table 9 shows the p values of the two-sample K-S tests between every two optimal solutions. All the p values in the test results are larger than 0.05, indicating all the optimal solutions follow the same type of distribution.

Table 9. The Kolmogorov–Smirnov test results (p values) between every two optimal solutions.

	Opt 1	Opt 2	Opt 3	Opt 4	Opt 5
Opt 1	-	0.538	0.377	0.519	0.493
Opt 2	0.538	-	0.421	0.361	0.445
Opt 3	0.377	0.421	-	0.396	0.404
Opt 4	0.519	0.361	0.396	-	0.578
Opt 5	0.493	0.445	0.404	0.578	-

CONCLUSION

The Phase III research makes contribution to optimizing candidate GSI and modeling the runoff with GSI implementation in a large spatial scale, which are challenges in current surface transportation planning and stormwater management. The methods developed for solving these two issues also provide the decision support for improving and optimizing the stormwater management system in surface transportation planning, and both of them are transferrable to other locations.

The optimization minimizes environmental, economic, and human health impacts at the system level associated with the construction, operation, and maintenance of GSI. For the case study of Tampa, the optimal solutions were found as a certain amount of candidate GSI selected with the information of location, size, and type. The candidate GSI in the optima can effectively lower the nutrient discharge to Tampa Bay below the limits, with the minimal environmental and economic impacts of the implementation of the candidate GSI. Besides, this project shows that some features of the road transportation system like its low terrain and high impervious rate are key factors to determine the location and type of candidate GSI.

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