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Optimal planning of natural stormwater solutions using a composite Gini coefficient: A watershed assessment of hydrological, environmental, social, and economic efficiency

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Abstract

A robust multi-functional framework for widespread planning of nature-based solutions (NBS) must incorporate components of social equity and hydro-environmental performance in a cost-effective manner. NBS systems address stormwater mitigation by increasing on-site infiltration and evaporation through enhanced greenspace while also improving various components of societal well-being, such as physical health (e.g., heart disease, diabetes), mental health (e.g., post-traumatic stress disorder, depression), and sense of place. However, current optimization tools for NBS systems rely on stormwater quantity abatement and, to a lesser extent, economic costs and environmental pollutant mitigation. Therefore, the objective of this study is to explore how NBS planning may be improved to maximize hydrological, environmental, and social co-benefits in an unequivocal and equitable manner. Here, a large-scale NBS watershed was calibrated to local conditions using standard hydro-environmental modeling and optimized according to the traditional NBS planning paradigm (i.e., on the basis of stormwater abatement, pollutant load reduction, and economic efficacy). The resulting NBS allocation was then integrated with spatial properties of social deprivation through a novel framework involving the Area Deprivation Index (ADI) and a multi-functional Gini coefficient. This framework allows us to better understand and optimize how social, environmental, and hydrological impacts differ across human populations and landscapes as a function of cost. By embedding social equity as an explicit optimization objective within the fabric of the NBS planning process, this study provides a strategic opportunity for addressing social justice and spurring community buy-in toward balanced NBS systems.

Highlights

1. Nature-based solutions (NBSs) are traditionally planned to maximize stormwater abatement potential while minimizing implementation costs.
2. Research has demonstrated the capability of NBSs to address issues of societal well-being, such as improved mental and physical health.
3. A novel framework is proposed and demonstrated to combine hydro-environmental modeling with social deprivation using the Gini coefficient.

Keywords:

→ area deprivation index (ADI)
→ Gini coefficient
→ low impact development
→ multi-objective optimization
→ storm water management model (SWMM)
→ social equity

1 Introduction

Nature-based solutions (NBSs) are expected to become a central tool for climate change adaptation, and we necessitate enhanced approaches to synchronize resiliency goals associated with societal well-being, environmental justice, and natural hazard mitigation. NBSs describe a collection of sustainable management approaches that emulate natural processes to address hydro-environmental hazards while simultaneously providing social and ecosystem benefits. NBSs have evolved within the literature to encompass the urban drainage concepts of green infrastructure (GI), low-impact development (LID), best management practices (BMPs), sustainable urban drainage systems (SuDs), water-sensitive urban design (WSUD), and blue-green infrastructure (BGI) (Ruangpan et al., 2020). As such, the predominant modeling schemes used for NBS planning have typically highlighted hydrological efficacy with less attention to social characteristics (Zhang and Chui, 2018). However, we know that the location of human settlements can influence several social factors that have been linked to NBS co-benefits, such as improvements in communal well-being, mental health, recreation, and physical health (Alves et al., 2019; Fenner, 2017; Li et al., 2017). By providing enhanced greenspaces and social gathering places, NBSs have been linked to a reduction in cardiovascular disease, diabetes, cancer, mental disorders, and chronic respiratory diseases, which are disproportionately higher among racial and ethnic minorities and the socioeconomically disadvantaged (Astell-Burt and Feng, 2021; Brown et al., 2016; Fuertes et al., 2014; Gascon et al., 2016; Maas et al., 2009; Mitchell and Popham, 2008; Ray and Jakubec, 2014). As such, we must integrate hydro-environmental and social characteristics to realize the full benefits of NBSs.

At the local scale (i.e., laboratory-, plot-, neighborhood-scale), NBS technologies have shown great promise in addressing both stormwater abatement goals and socio-environmental co-benefits

(Jato-Espino et al., 2016; Kabisch et al., 2016; Loperfido et al., 2014). At the regional scale, however, widespread use of NBS technologies has been limited due to a lack of understanding the complex interactions between physical characteristics and social conditions (Lim and Welty, 2017; Zhang and Chui, 2018). When planning for NBS systems, there will exist inherent tradeoffs between spatial priority and functionality that must be considered. The optimal spatial configuration of an NBS system is a function of overlapping rainfall patterns, watershed properties, equity factors, environmental triggers, ecological considerations, socio-demographics, risk and vulnerability, and other underlying principles that have not been fully elucidated (Perez-Pedini et al., 2005). Traditionally, NBS optimization schemes have continued to prioritize drainage characteristics in lieu of social functionality throughout space, while assuming such co-benefits will somehow propagate naturally throughout the system (Ruangpan et al., 2020; Zhang and Chui, 2018). In this way, NBS multi-functionalities are not included as an explicit representation of their full locational benefits, thus limiting the maximum potential of NBSs to mitigate cross-cutting issues within the urban fabric. A right first step toward fully encompassing NBS multi-functionalities is to represent disparate phenomena as functions of space and to quantify their tradeoffs through the lens of multiple, overlapping disciplines.

In the age of the Anthropocene, where hydrologic, environmental, and social processes are being influenced and altered by human patterns, we are starting to study Earth systems outside of the traditionally-fixed vacuum of ideal physical boundary conditions. Researchers are beginning to couple biophysical processes with societal influences through the flourishing fields of socio-hydrology, coupled human and natural systems (CHANS), socio-ecology, and others (Blair and Buytaert, 2016). The hydrological community is suggesting that we address socio-environmental justices by integrating transdisciplinary variables into watershed modeling frameworks. Much of the recent progress in socio-hydrology has evolved from a combination of exploratory frameworks (i.e. feedbacks, causal relationships, patterns) with water balance models and system dynamics (Kuil et al., 2016; Pande and Sivapalan, 2017). While such couplings have been widely noted within the literature, they are seldom quantitated and considered holistically in NBS management frameworks (Ruangpan et al., 2020).

NBS systems are instead typically planned with either simplified data-overlay methods for defining hot-spots of vulnerable locations or complex hydro-dynamic programs that prioritize stormwater volume abatement over social functionalities (Madureira and Andresen, 2014; Zhang and Chui, 2018), with the latter being limited in their scale of analysis due to large data requirements and computational difficulties (Barco et al., 2009). By relying on complex modeling tools (i.e., SWMM, MIKE-URBAN), most NBS studies have tended to neglect the social dimension altogether in favor of earth-system processes, thereby lacking optimal configurations for capturing holistic co-benefits (Kandakoglu et al., 2019). For these reasons, widespread adoption of green infrastructure has generally remained stunted, despite the ongoing evidence that NBSs provide efficient stormwater mitigation, lower costs in comparison to traditional grey infrastructure, and numerous social benefits (Golden and Hoghooghi, 2018; Madureira and Andresen, 2014). A recent state-of-the-art review described how consideration of multiple co-benefits has been increasingly valued as a desirable goal throughout the NBS literature, yet the majority of NBS planning has continued to prioritize stormwater abatement, due in part to a lack of integrated socio-hydrological frameworks (Ruangpan et al., 2020). We thereby have substantial knowledge gaps regarding informed NBS optimization (Golden and Hoghooghi, 2018; Kabisch et al., 2016), as interactions between NBS phenomena and the social conditions with which they aim to address are poorly represented in our existing frameworks (Lim and Welty, 2017). As such, explicit representation of the social co-benefits of NBS systems is one of the most critical barriers to overcome for widespread success in this field (Adib and Wu, 2020).

In addition to a lack of robust representation of social characteristics within NBS optimization frameworks, the decision to implement NBS within a given locale is also highly dependent on stakeholder buy-in (Van de Meene et al., 2011; Wihlborg et al., 2019). NBSs are unlike traditional stormwater infrastructure due to regular human interaction with the greenspaces, which impacts social well-being. Many NBS technologies, such as roof gardens or rainwater harvesting systems, function as an optimal unit when implementation occurs on both public and private properties. In this respect, local community buy-in is essential for achieving widespread NBS adoption. Studies have demonstrated how NBS implementation continues to be limited due to the inability for decision-makers to visualize overlapping co-benefits at the local scale (Adib and Wu, 2020; Liu and Jensen, 2018; Sarabi et al., 2019; Van de Meene et al., 2011; Wamsler et al., 2020; Wihlborg et al., 2019). Studies have also shown that attitudes regarding NBSs are improved when stakeholders can readily identify how NBS solutions will benefit their locale in a manner that extends beyond stormwater performance (Liu and Jensen, 2018; Sarabi et al., 2020; Wamsler et al., 2020). In other words, robust NBS implementation will not occur until city planners are able to identify and prioritize the multiple co-benefits involved in the NBS system. As such, in order to fully capture the multi-functionalities of NBS systems and improve implementation, we necessitate innovative optimization frameworks encompassing the variety of physical and social functionalities associated with NBSs.

Current stormwater management within the study area (Houston, Texas, USA) is based on a ‘worst-first’ framework (Despart, 2019), where hydrological improvements are prioritized according to flood risk reduction and the number of persons benefited, irrespective of their socio-economic conditions. Such frameworks do not address inherent vulnerabilities within the populations served to consider human aspects, such as ability to recover from a storm or the reinforcing impacts of hydro-environmental hazards on socio-economics. This study re-shapes the NBS planning process by transcending beyond flood risk to also include components of social characteristics as a policy-making mechanism. Here, a novel equity-based indexing framework is proposed to better understand how we might optimize social and physical functionalities of NBS systems as a function of trans-disciplinary characteristics. Specifically, we explore the spatial tradeoffs associated with NBS allocation by first optimizing a local watershed-scale model according to traditional metrics of efficacy (e.g., cost efficiency, hydrological runoff reduction, and pollutant load reduction). We then identify the statistical dispersion of social vulnerability using the Area Deprivation Index (ADI), which is a spatial account of neighborhood disadvantage according to United States census characteristics. The ADI is incorporated into the optimization scheme using a novel area Gini coefficient and Lorenz curve. This framework is intended to spur the positive connection of social and physical influences within robust NBS planning.

2 Materials and Methods

2.1 Area Deprivation Index

The ADI was introduced in 2016 as a proxy indicator of socio-economic status from census results that have been curated to reflect the highest risk factors associated with long-term health (Knighton et al., 2016). The ADI is primarily used within the medical literature to measure social determinants that have been shown to influence public health issues, such as cancer rates (Kurani et al., 2020), hospital admissions (Hirshberg et al., 2019; Ingraham et al., 2021), asthma (Nkoy et al., 2018), obesity (Ludwig et al., 2011), diabetes (Addala et al., 2021), mental health (Martikainen et al., 2004), and mortality (Chamberlain et al., 2020; Singh, 2003), each of which are impacted by NBS systems (van den Bosch and Ode Sang, 2017). The ADI merges characteristics of income, employment, education, and housing from the United States census to represent social disadvantage (Kind and Buckingham, 2018), which have been shown collectively to influence communal health (Link and Phelan, 1995).

An advantage of using the ADI for NBS planning, as opposed to other social indices, involves its highly-granular geospatial scale. The ADI provides a unique measurement of social deprivation for each census block group within the United States. Other standard metrics of social vulnerability, such as the Center for Disease Control (CDC) Social Vulnerability Index (SVI) (Flanagan et al., 2020), are delineated at the census tract-scale, thereby lacking spatial heterogeneity to assess key differences at the local-scale. [Note: Census tracts are subdivisions of counties encompassing approximately 4,000 residents within each bound. Block groups are subdivisions of census tracts encompassing approximately 250-550 housing units, demarcated by local streets (Schlossberg, 2003).]

The ADI for the study area was downloaded from the University of Wisconsin's Neighborhood Atlas for year 2019 (Kind and Buckingham, 2018). The weighted ADI values within each spatial unit are represented at the national-level by a percentile (1-100) and at the state-level by a decile (1-10), with lower values denoting greater disadvantage (University of Wisconsin School of Medicine and Public, 2019). For example, an ADI value of 1 on the national-scale represents an area that is more disadvantaged than the remaining 99% of census blocks within the nation. At the state-scale, an ADI of 1 implies that the given census block is more disadvantaged than 90% of the other census blocks within that state.

Here, the national-level ADI was used to depict spatial variation of social inequity throughout the White Oak Bayou (WOB) watershed in Houston, Texas, USA. The WOB watershed was chosen for this case study as it contains a highly-heterogeneous representation of socio-economic status, as represented in **Fig. 1**.

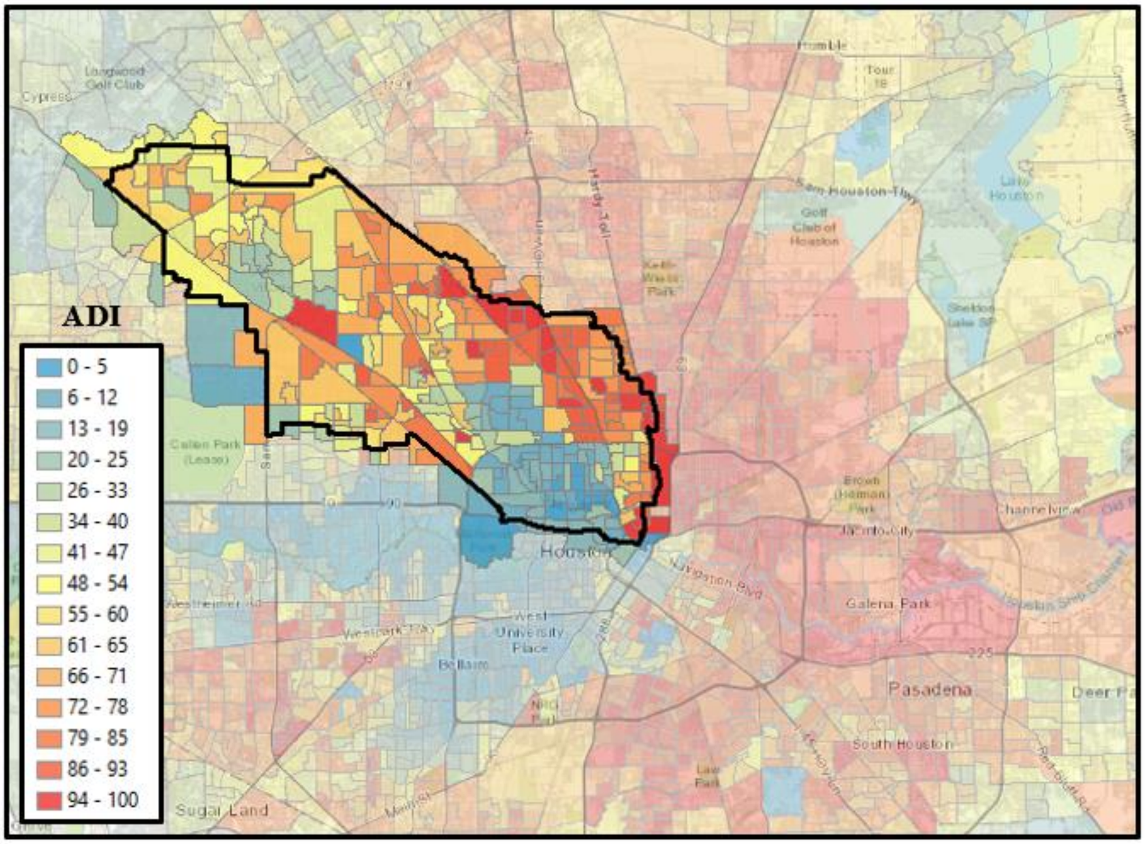

Fig. 1. Area deprivation index for the White Oak Bayou watershed.

2.2 Hydro-environmental SWMM Model

2.2.1 Hydrological Modeling

The basin model for the WOB watershed was initialized using the HMS-PrePro tool, which rapidly delineates a watershed into subcatchments according to the local terrain, connects hydrological topology in a format consistent with standard hydrological modeling software, and estimates common hydrological parameters to represent basin infiltration, runoff, and channelized routing of flow (Castro and Maidment, 2020). The Green-Ampt method was used to represent infiltration losses within each subcatchment according to local empirical values used in FEMA-effective hydrology models for the WOB watershed (HCFCD, 2019) (initial content = 0.067, saturated content = 0.46, suction = 3.553 inches, conductivity = 0.032 inches/hour). The SWMM software routes overland flow to the subcatchment outlet using a property called the 'characteristic width', which is defined as the subcatchment area divided by the average maximum overland flow length (Rossman and Huber, 2016). The longest flow path for each subcatchment was calculated in HMS-PrePro according to 2018 LiDAR at 10-centimeter resolution (TNRIS, 2019). The time of concentration for each subcatchment was calculated using the TR-55 methodology for urban watersheds (USDA, 1986).Other principal inputs for modeling subcatchments in SWMM include average land use, impervious coverage, subcatchment area, and terrain slope, which were each estimated using HMS-PrePro.

PCSWMM version 7.4.3240 (Hamouz et al., 2020), which is a proprietary software designed as a user-friendly interface to the Environmental Protection Agency (EPA) SWMM program, was used to convert the preliminary basin into a SWMM model. To route flow through the watershed stream network, the PCSWMM Transect Tool was used to create average cross-sections for each system channel from the 2018 LiDAR elevation model (CHI, 2014). Design storm data for the Houston region was obtained from Barrett (2019) and COH (2019) to represented the latest Atlas 14 precipitation frequency estimates in Texas, according to the National Oceanic and Atmospheric Administration (NOAA) (Perica et al., 2018). The rainfall intensity values for the Houston-area were used to develop intensity-duration-frequency (IDF) curves in PCSWMM for varying annual exceedance probability (AEP) storm events (summarized in **Table S.1**). The IDF curve estimates a frequency of occurrence for extreme precipitation events, which is commonly used to design urban stormwater infrastructure (Koutsoyiannis et al., 1998).

2.2.2 Pollutant Load Modeling

The event mean concentration (EMC) method was used to estimate non-point water pollution within each subcatchment according to

$$EMC_s = \frac{\int C_s Q_s dt}{\int Q_s dt}, \tag{1}$$

where EMC_s is the event mean concentration, C_s is the standard concentration of a target pollutant, and Q_s is the runoff volume for each subcatchment, s, changing over simulation time t.

Local stormwater monitoring data was obtained from the National Stormwater Quality Database (NSQD), which contains public water quality meta-data from over 9,000 runoff events for approximately 200 municipalities in the United States, including 41 monitoring stations within Harris County, Texas (Pitt et al., 2015). Since the GreenPlan-IT algorithm searches for the most cost-effective solution according to an individual pollutant type (further described in **Section 0**), total suspended solids (TSS) were chosen as the criteria pollutant due to the strong adsorption effects of TSS on other contaminants (Liu et al., 2019; Rossi et al., 2006). Pooled values of TSS concentrations were obtained for each land use type within the NSQD, as summarized in **Table S.2**. In watershed-scale modeling, pooled load concentrations are common and have not been shown to pose a significant impact on the resulting model outcomes, particularly when the purpose of analysis is for comparison between scenarios (Lin, 2004; White et al., 2015).

The land use values in the WOB basin model were obtained from the 2016 National Land Cover Database (NLCD), which contains 16 unique land classifications based on the modified Anderson Level II scheme (Yang et al., 2018). The NLCD land uses were re-classified to correspond with the five land use types used in the NSQD (see **Table S.2**). The removal efficiency for each of the NBS types modeled in this study were obtained from the 2020 International Stormwater BMP Database (Clary et al., 2020), which corresponds well with average removal efficiencies in the NBS literature for watershed-scale stormwater modeling (e.g., Eckart et al. (2017); Liu et al. (2015)).

2.2.3 NBS Water Balance Modeling

EPA's SWMM engine calculates the water balance for NBS-driven systems using a nonlinear reservoir model (Chen and Shubinski, 1971) according to a unique set of infiltration, storage, and evaporation properties that describe, on a per-unit-area basis, how NBS structures impact hydrological behavior. A subset of zones and water fluxes as a function of NBS behavior is depicted in **Fig. 2**.

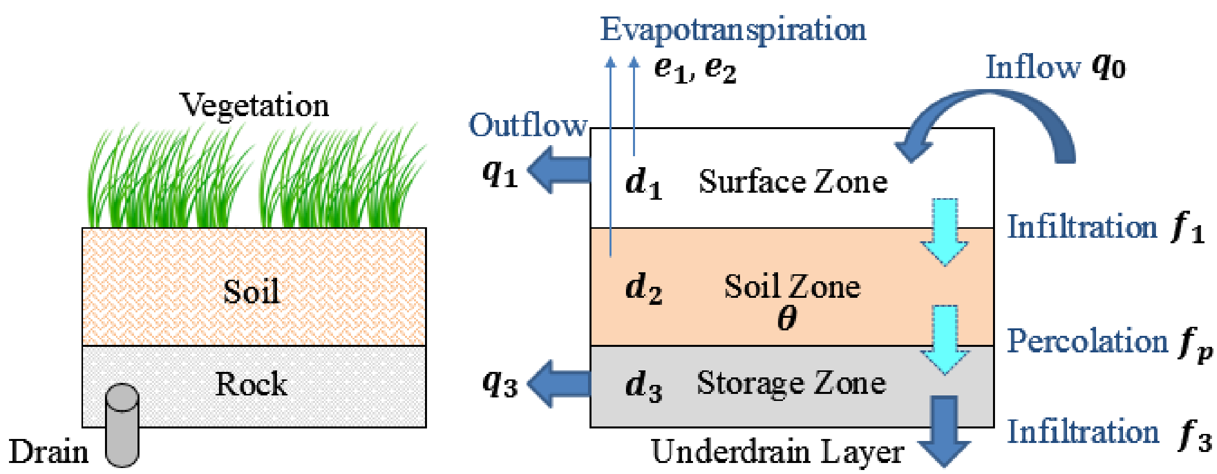

Fig. 2. Conceptual model of NBS water balance processes.

The water fluxes are defined by Rossman and Huber (2016):

$$\frac{\partial d_1}{\partial t} = q_0 - e_1 - f_1 - q_1, \tag{2}$$

$$d_2 \frac{\partial \theta}{\partial t} = f_1 - e_2 - f_\mathrm{p}, \tag{3}$$

$$\frac{\partial d_3}{\partial t} = f_\mathrm{p} - f_3 - q_3, \tag{4}$$

where d_1 is the depth of ponded water on the surface zone with outflow q_1 (cfs), d_2 is the depth of the soil zone with moisture content θ, d_3 is the depth of the storage zone with outflow q_3 (cfs), q_0 describes the inflow to each NBS cell (cfs), e_1 and e_2 represent the evapotranspiration from the surface zone and the soil zone, respectively, f_1 describes infiltration between the surface and soil zone, f_p is percolation between the soil and storage zone, and f_3 is infiltration from the storage zone to the underdrain layer.

The flux terms (q, e, f) are functions of the water content within each layer and subcatchment site conditions. The set of equations is solved at each runoff time step, according to the Green-Ampt method, to calculate how the inflow hydrograph to the NBS unit is converted to a runoff hydrograph, further described by Rossman (2014).

Within NBS systems, the surface zone represents the ground surface, which stores excess inflow and generates outflow either overland or to an adjacent drainage system. The soil zone is comprised of an engineered soil mixture that allows water to percolate into the underlying zone, which consists of rock and gravel for additional storage. The underdrain system conveys water out of the storage layer and into an engineered outlet. The three NBS features used in this case study (bioretention cells, porous pavement, and tree boxes) are summarized in **Table S.3** as a function of the representative water balance layers modeled in PCSWMM. In the WOB case study, tree boxes were modeled as bioretention cells with no outflow drain.

Various input parameters are also required within a SWMM model to describe the engineered design of local NBS features (e.g., conductivity rate, vegetation volume, clogging properties, surface roughness, etc.), which were obtained from the City of Houston design guidelines for low impact development (COH, 2019b), as summarized in **Table S.4**.

2.2.4 Calibration & Validation

The hydrological basin parameters were calibrated to observed streamflow measurements from United States Geological Survey (USGS) stream gauges #08074020 and #08074500 (USGS, 2021a, 2021b). One year of daily precipitation values were obtained from the Harris County Flood Warning System (HCFWS) precipitation gauges #530, #535, #550, #555, #560, #570, #582, #590, and #595 (HCFCD, 2021), encompassing the totality of the White Oak Bayou watershed as shown in **Fig. 3**.

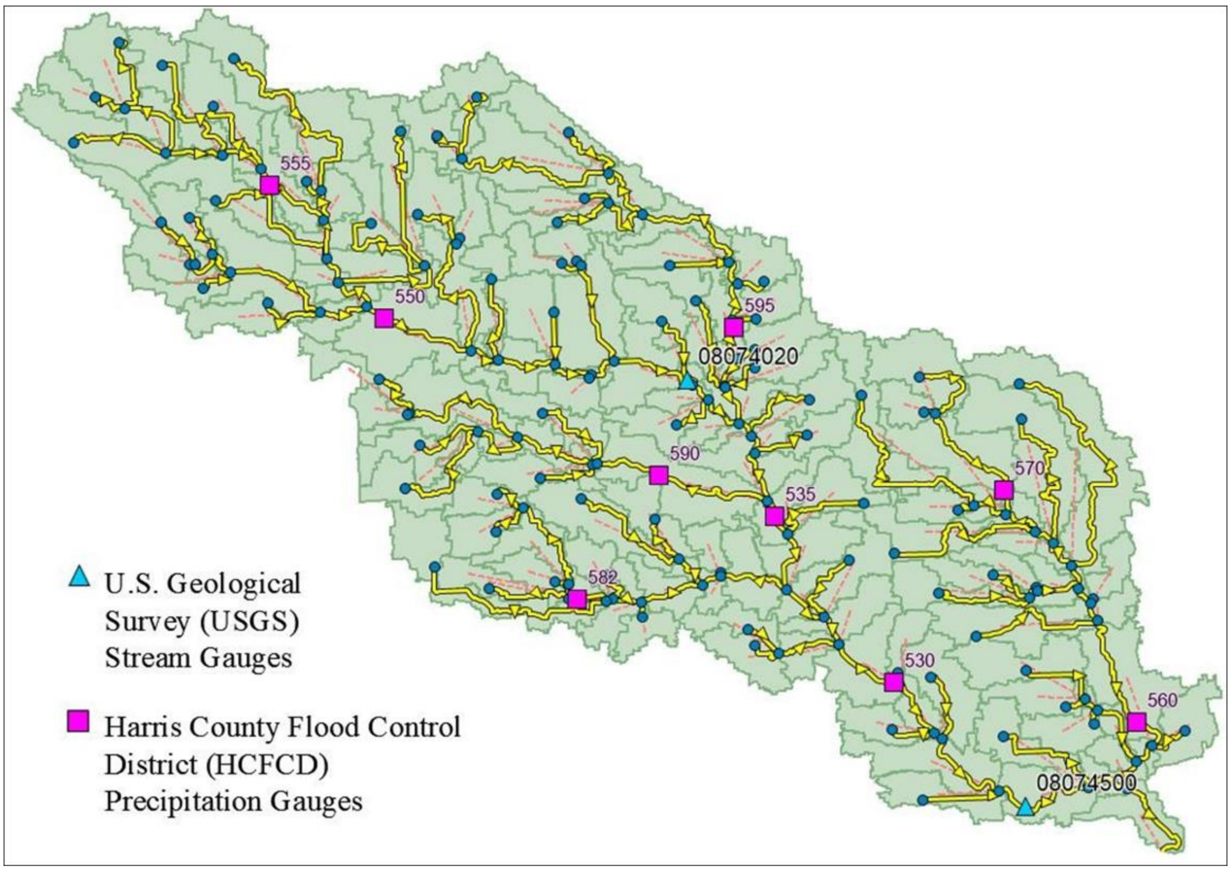

Fig. 3. PCSWMM basin model, stream gauges, and precipitation gauges for WOB.

The first six-months of precipitation data (October 2, 2020 – March 2, 2021) were used to calibrate the model, while the latter six-months of data (March 3, 2021 – August 2, 2021) were used to validate the model. The PCSWMM sensitivity-based radio tuning calibration (SRTC) tool was used to aid in identifying the most sensitive parameters within the model, according to user-identified uncertainty, and for calibrating the model to match observed streamflow (CHI, 2015). The annual set of hydrographs for the basin model was disaggregated for wet weather conditions with a criterion of at least 500 cfs flow for a minimum of 4 consecutive hours (**Fig. S.1**), resulting in ten unique storm events for calibration (**Table S.5**) and eight unique storm events for validation (**Table S.6**). The wet weather flow hydrographs were calibrated using the PCSWMM SRTC tool by selecting uncertainties for control parameters based on their data source and sensitivity gradient, per guidelines proposed by Choi and Ball (2002) and James (2003). The gradients for the parameters with the greatest model sensitivity are shown in **Fig. S.2**. The basin model was then simulated with the calibrated parameters and compared to observed streamflow and resulting error metrics to measure goodness-of-fit (**Fig. S.3**).

The error metric employed in this study was the integrated square error (ISE), which amalgamates differences between observed and calibrated values according to overall storm runoff volume, peak flow, mean flow, and the hydrograph time to peak (James, 2003). The ISE is advantageous over the traditional Nash-Sutcliffe efficiency (NSE) or coefficient of determination (R^2) because these latter error metrics are both sensitive to outliers and tend to converge on one measure of hydrological efficacy (i.e., total runoff *or* peak flow *or* average runoff) (CHI, 2020). The ISE is recommended for large-scale watershed planning due to its capability to assess goodness-of-fit over a range of historical rain events and hydrograph parameters, rather than potentially biasing the model to one specific event or metric of performance (CHI, 2015). Moreover, the ISE is beneficial in urban watersheds that are modeled without sub-surface flow because sewer system hydraulics may be indirectly calibrated using the ISE, whereas the NSE is dominated solely by overland flow conditions (Sarma et al., 1973).

The ISE is expressed as:

$$ISE = \frac{\sqrt{\sum\left(y_{obs}^{i} - y_{comp}^{i}\right)^2}}{\sum y_{obs}^{i}}, \tag{5}$$

where y_{obs}^{i} is the observed value, and y_{comp}^{i} is the computed value for the i-th observation. Then, the rating of the resulting ISE error metric may be defined on a qualitative scale, as defined by Sarma et al. (1973), such that ISE ≤ 3 = Excellent, 3 < ISE ≤ 6 = Very Good, 6 < ISE ≤ 10 = Good, 10 < ISE ≤ 25 = Fair, and ISE > 25 = Poor.

The model calibration and validation hydrographs and ISE error metrics are demonstrated in supplementary materials (**Fig. S.1** – **Fig. S.3** and **Table S.5** – **Table S.6**), respectively.

2.3 Spatial Allocation Optimization

A decision support tool, called GreenPlan-IT, was used to optimize the fully-calibrated watershed model according to levels of runoff reduction, pollutant load abatement, and cost effectiveness (Wu et al., 2019). The workflow for the optimization scheme is demonstrated in **Fig. 4**, adapted from (SFEI, 2018). The optimization tool compares the performance of various NBS strategies to the baseline scenario, which represents watershed conditions prior to NBS implementation. Model performance is defined by three objectives: 1) minimized total relative cost of NBS implementation, 2) maximized reduction in hydrological runoff, and 3) maximized abatement of pollutant loads within the study area. GreenPlan-IT couples the nondominated sorting genetic algorithm (NSGA-II) with the EPA SWMM software according to the Pareto front solution (SFEI, 2018). The GreenPlan-IT package combines several unique tools that operate in succession to identify the optimal spatial allocation of NBS features, including:

1) GIS-based Site Locator Tool (SLT): Merges spatial characteristics of NBS types with regional geospatial information to identify all possible NBS locations within the study area.

2) EPA SWMM Basin Model: Establishes baseline conditions for runoff and pollutant loading prior to NBS optimization.

3) GreenPlan-IT Optimization Tool (GPOT): An executable file that runs through the user's command prompt to identify optimal combinations of NBS types within each catchment area according to a cost-benefit analysis (where costs are defined by the user, and benefits are calculated using SWMM to assess the reduction in stormwater runoff and pollutant loads for many simulations).

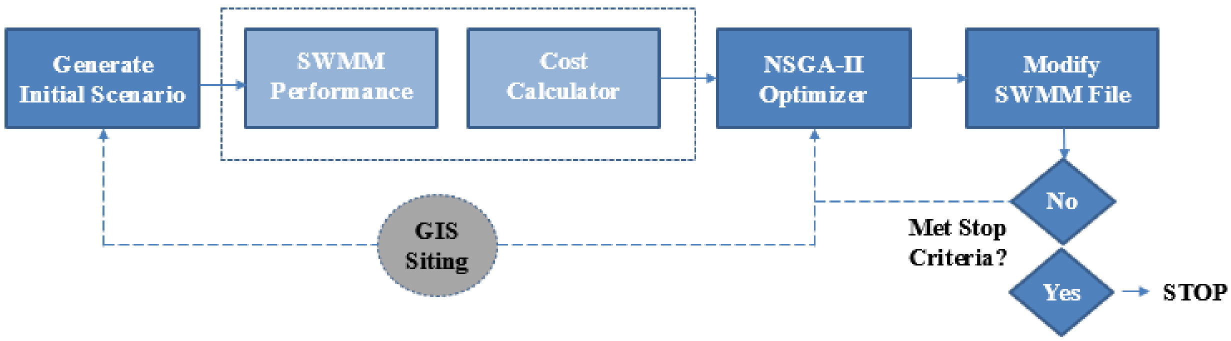

Fig. 4. GreenPlan-IT optimization workflow.

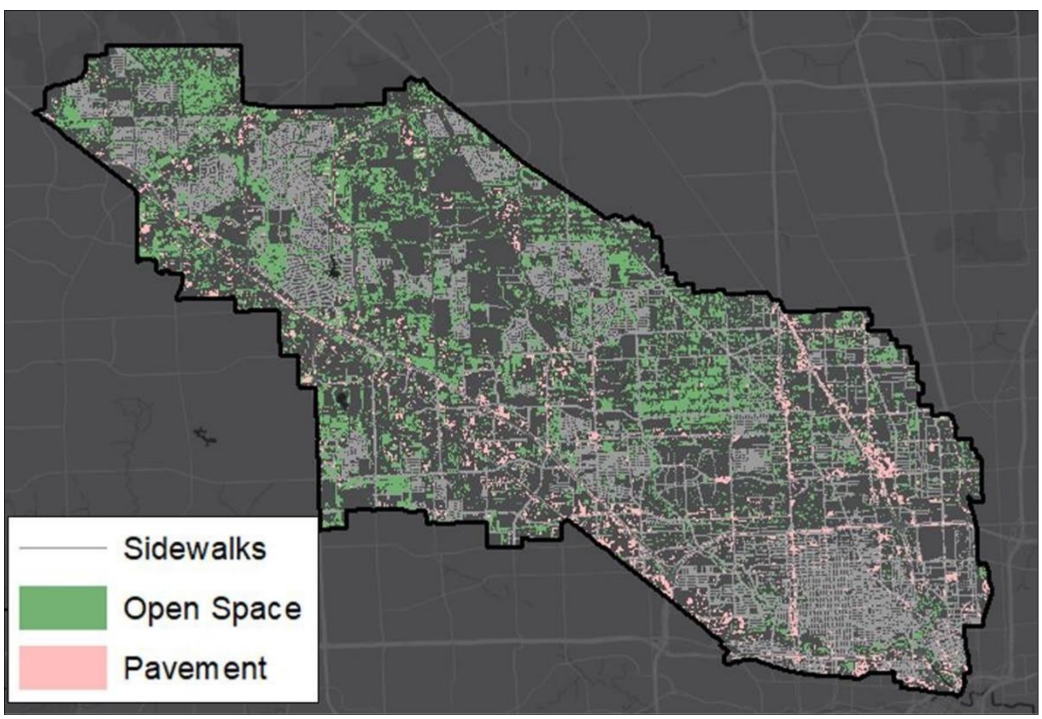

Fig. 5. Geospatial siting of potential NBS locations in the WOB watershed.

The GIS-based SLT was used to identify all potential locations of NBS features within the WOB watershed, as shown in **Fig. 5**. Potential locations for bioretention cells, permeable pavement, and tree boxes were defined according to open space land use parcels, areas of existing pavement, and adjacent land near existing sidewalks, respectively. Corresponding data layers were obtained from the City of Houston GIS Data Hub (COH, 2021). Baseline flow and TSS loads were quantified within the SWMM model for various design storm events, as described in **Section 2.2**. The SLT output serves as a spatial constraint for the GPOT, which executes several thousand SWMM models according to unique spatial allocations of NBS features within the permissible areas (i.e., the shaded areas shown in **Fig. 5**). The GPOT compares the performance of various NBS strategies to the baseline scenario, which represents watershed conditions prior to NBS implementation. Model performance is defined by three objectives: 1) minimized total relative cost of NBS implementation, 2) maximized reduction in hydrological runoff, and 3) maximized abatement of pollutant loads within the study area.

Relative cost estimates for the case study were obtained from the EPA National Stormwater Calculator (NSWC), which provides annual costs for NBS implementation and maintenance within unique geographical regions. At the time of study, the NSWC cost estimates for the Houston-area included: pervious pavement = \$8.68/SF, bioretention cells = \$6.07/SF, and tree planter boxes = \$9.46/SF (Bernagros et al., 2021). The GPOT uses two input files to compare NBS scenarios with the baseline SWMM model. The first input file contains the total acreage and percent impervious coverage for each subcatchment and the maximum number of possible NBS sites per subcatchment from the GIS-based SLT, as summarized in **Table S.7**. The second input file describes sizing parameters, where the NBS features were assigned a uniform unit area and width of 500 SF by 20 FT, 5000 SF by 50 FT, and 60 SF by 6 FT for bioretention cells, pervious pavements, and treeboxes, respectively.

The NSGA-II algorithm, originally presented by (Deb et al., 2002), searches for the optimal solution among numerous possible scenarios by first modeling a random set of NBS placements and comparing their outputs for non-dominance. Non-dominance occurs when a solution performs no worse than any other solution for all objectives (e.g., cost, runoff, and pollutant load efficiency) and also performs better than all other solutions within the cohort for at least one objective. This cohort (known as a generation), then sorts each of the sub-routines within the series (known as populations) for non-dominance. Another generation is run using the previous generation's non-dominant solutions and relative population samples. This iteration continues until the system either reaches a maximum number of generations or until no further changes are observed between two consecutive populations. The primary GreenPlan-IT tool, which was designed for use in the greater San Francisco Bay area, uses a threshold of 200 generations, each with a population size of 100, for a maximum of 20,000 watershed simulations (SFEI, 2018). The GreenPlan-IT tool was modified in concert with the tool developers for use in Houston, Texas, which resulted in an NSGA-II stop criteria of 100 generations, each with a population size of 250 model runs. As a result of this collaboration, it is our understanding that future versions of GreenPlan-IT will be released to allow application in other large watersheds, such as the WOB. The model outputs of the optimization tool are plotted as a function of cost (x-axis) versus runoff or load reduction (y-axis), resulting in a Pareto curve (see **Section 3.1**Error! Reference source not found.). Each point along the convex of the Pareto curve (known as the Pareto front) represents a unique, quasi-optimal solution for NBS spatial allocation according to the cost and reduction targets located on the Pareto curve axes (Wu et al., 2019).

2.4 Multi-objective Gini Index

The Gini coefficient, which was originally identified by Gini (1912), is a statistical representation of inequality across a population. The Gini coefficient is based on the Lorenz curve, depicted in **Fig. 2**, which describes the cumulative proportion of values along the x-axis compared with the cumulative proportion of values along the y-axis. Within the social sciences, the Gini-based approach is commonly used to assess the degree of matching between population (x-axis) and income/wealth (y-axis) for economic purposes to quickly compare and rank disparate geographic entities (Giorgi and Gigliarano, 2017).

In a perfectly-equal scenario, the distribution of income matches the distribution of the population, shown as the diagonal line in **Fig. 2**. In a more realistic scenario, the normalized percentage of population to percentage of household income typically follows an exponential distribution, known as the Lorenz curve, which delineates state spaces **A** (e.g., the inequality gap) and **B** (e.g., the actual income distribution) in **Fig. 6**.

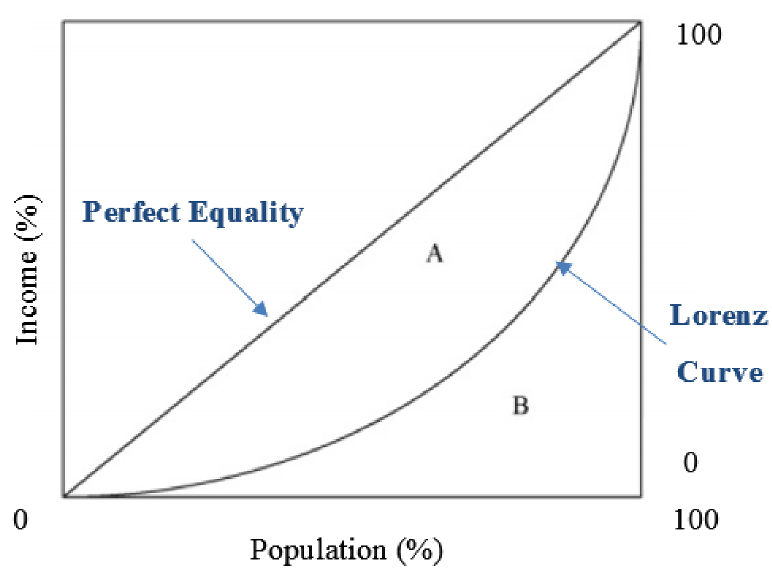

Fig. 2. Conceptual graph of Gini-based equality and Lorenz curve.

The Gini coefficient (G) is expressed graphically by

$$G = \frac{A}{(A+B)}, \tag{6}$$

where A represents the total area between the line of equality and the Lorenz curve distribution, and B represents the area between the Lorenz curve and the base axes.

A numerical form of the Gini coefficient (G_i) is given by

$$G_i = 1 - \sum_{i=1}^{n} (Y_i - Y_{i-1})(X_i + X_{i-1}), \tag{7}$$

where X_i is the cumulative percentage of the variable on the x-axis, and Y_i is the cumulative percentage of the variable on the y-axis, for data point i, from i=1 to i= n total data points.

Gini coefficient value ranges from 0 to 1, where 0 indicates absolute equality, and 1 represents absolute inequality. Due to the popularity of the Gini coefficient to quickly identify statistical differences in equality, studies have begun applying this economic concept to issues of energy allocation (Jacobson et al., 2005; Saboohi, 2001), environmental inequity (Boyce et al., 2016; Heerink et al., 2001; White, 2007), water resources allocation (Cho and Lee, 2014; Du et al., 2021; Hu et al., 2016; Yan et al., 2018), flood drainage rights (Zhang et al., 2020), and other topics regarding distribution of limited resources (Josa and Aguado, 2020).

Many of the recent applications of the Gini concept to issues of environmental concern utilize the area-based Gini coefficient. The area-based Gini ("AR-Gini") compares a social metric, calculated on an area basis, to a distributed social good, calculated on a resource basis (Druckman and Jackson, 2008). The AR-Gini may be used to compare spatial patterns of space-based resources and population-based social metrics to reveal internal relationships, improve planning frameworks, and identify useful cross-disciplinary spatial indicators. An example of using the AR-Gini coefficient beyond the traditional scope of economic wealth disparity is given by Sun et al. (2010) where wastewater discharge permitting is optimized using the Gini index and a multi-criteria assessment of land, population, income, and environmental capacity. In this study, the conflict between wastewater efficiency and social equality is bridged by balancing tradeoffs between various policy-making goals amidst limited resources (Sun et al., 2010).

The method presented here uses a novel representation of the AR-Gini to advance sustainability planning by combining hydrological, environmental, and social efficiencies within NBS spatial allocation optimization. In this study, the cumulative area of NBS allocation as a proportion of each subcatchment area is plotted on the y-axis, normalized on a scale from 0-100. Unique evaluation indicators (i.e., stormwater runoff, stormwater quality, and social equity) are then plotted on the x-axis, such that each potential optimization model contains three different Gini coefficients. Hydrological efficiency is represented as the percent difference of stormwater runoff volume between baseline and optimized conditions, as a function of cost. Environmental efficiency is described as the percent difference of pollutant load abatement between baseline and optimized conditions, according to cost. Social equity is a function of the average neighborhood disadvantage over the weighted area of NBS allocation within each subcatchment. By minimizing the sum of these multi-objective Gini coefficients, this novel approach reveals the state space of optimal hydrological efficacy and distribution of NBSs in socially-vulnerable locations.

Minimizing the Gini coefficient as a function of hydrological efficacy and social justice provides the novel framework for allocating NBSs according to both their hydrological functionality and also the social characteristics of persons that would be influenced by varying spatial arrangements. A high Gini coefficient would reveal that the distribution of NBSs using only hydrological efficacy does not maximize the multi-functional goals of improving societal health through improved access to nature. Here, several of the SWMM-based optimization scenarios from the GreenPlan-IT tool are calculated using the multi-functional Gini calculations, described below, to better understand the trade-offs between hydro-environmental/economic efficiency and spatial equality when planning watershed-scale NBS solutions. The first objective is to maximize the economic benefit efficiency of hydro-environmental spatial optimization. The second objective is to maximize social equity using a composite AR-Gini coefficient. In doing so, a hypothesis is generated from robust hydro-dynamic modeling, which is then tested against the spatial representation of social deprivation to elicit a numerical hypothesis of holistic NBS conditions that are optimally distributed to maximize urban greening in areas of highest social vulnerability.

The following equations are applied in deriving the multi-objective Gini coefficient:

$$\omega_s = \sum_{j=1}^{n} z_{js} A_j \,, \tag{8}$$

where ω_s is the allocation of NBS area per subcatchment s, n is number of unique NBS feature types j = bioretention cells, porous pavements, or tree boxes, z is the number NBSs per subcatchment, A_j is the area of each NBS feature type (A_j: bioretention cells = 500 SF, porous pavements = 5,000 SF, tree boxes = 60 SF),

$$\eta_s = \frac{\left(\frac{a_s - b_s}{a_s}\right) * 100}{\sum_{j=1}^{n} z_{js} A_j c_j}, \tag{9}$$

where η_s is the percent efficiency of hydro-environmental improvement between the baseline model, a, and the optimized model, b for each subcatchment s as a function of the cost for each NBS feature, c_j (c_j = \$6.07/SF, \$8.68/SF, \$9.46/SF for j=bioretention cells, porous pavements, and tree boxes, respective); a and b represent the total stormwater runoff volume (V_R, in million gallons) for hydrologic efficiency and the total pollutant load runoff (TSS, in lbs) for environmental efficiency, from SWMM modeling.

$$\mu_s = \frac{ADI_s}{\sum_{s=1}^{m} \omega_s}, \tag{10}$$

where μ_s is the percent of social inequality addressed by the optimized model according to the total NBS allocated area within each subcatchment, ω_s, for all subcatchments m, and the social inequality within the subcatchment is measured by the average spatial Area Deprivation Index (ADI) score within each subcatchment ADI_s.

To eliminate differences in measurement units and magnitudes among evaluation choices, each indicator is then normalized on a scale of 0 to 100 per

$$\tilde{x} = \frac{x - x_{min}}{x_{max} - x_{min}} * 100, \tag{11}$$

where $\tilde{x}$ is the normalized value of each x = hydrologic efficiency (η_s), environmental efficiency (η_s), and social equity (μ_s).

Consequently, the sum of the normalization series for each Lorenz curve axis is 100. The Gini coefficient is then calculated by:

$$Y_s = Y_{s-1} + \frac{\widetilde{\omega_s}}{\sum_{s=1}^{m} A_s} * 100, \tag{12}$$

$$X_s = X_{s-1} + \left(\frac{\widetilde{\eta_s}}{\sum_{s=1}^{m} \widetilde{\eta_s}} \mid \frac{\widetilde{\mu_s}}{\sum_{s=1}^{m} \widetilde{\mu_s}} \right) * 100, \tag{13}$$

$$G_i = 1 - \sum_{s=0}^{m} \left(X_s - X_{(s-1)}\right)\left(Y_s - Y_{(s-1)}\right), \tag{14}$$

where Y_s is the y-axis value on the Lorenz curve, X_s is the x-axis value on the Lorenz curve, A_s is the area of each subcatchment s, with total subcatchments m, and G_i is the Gini coefficient corresponding to the evaluation index i = runoff volume efficiency, pollutant load efficiency, or social equity distribution. X_s and Y_s are plotted on the Lorenz curve by sorting Y_s in ascending order, where X_0 and Y_0 each equal 0.

Finally, the composite optimization objective is represented by

$$Optimization\ Objective\!: \min\left(\frac{\sum_{i=1}^{I} G_i}{I}\right), \tag{5}$$

where G_i is the multi-functional Gini coefficient average for each indicator, i, for a total number of indicators I.

In summary, the following steps are applied to calculate the composite Gini index for amalgamating a series of NBS efficiency indicators according to both social deprivation and hydro-environmental risk:

1. Select a set of potential NBS allocation scenarios according to hydro-environmental SWMM-based optimization modeling.
2. Calculate Lorenz curve values for each efficiency indicator (hydrologic, environmental, and social) and NBS scenario.
3. Plot the Lorenz curves and calculate the individual Gini coefficients.
4. Aggregate the objective functions and compare Lorenz curves according to the multi-criteria Gini coefficient.
5. Identify the greatest distribution of social equality and hydro-environmental efficiency by minimizing the optimization objective function.

3 Results and Discussion

3.1 Hydro-environmental Pareto Front Curve

The GreenPlan-IT optimization tool for the WOB watershed converged after 100 generations (i.e., series), each with approximately 250 population values per generation. The 2-, 5-, and 100-year rainfall events were chosen as representative design storms for demonstrating the hydro-environmental optimization results, as demonstrated in **Fig.7**. An example of planning for NBS expenditure of $1,000M is shown in the dashed lines where the optimal Pareto front results in a flow reduction of 3.22%, 3.62%, and 4.37% and a TSS pollutant load reduction 11.69%, 11.65%, and 9.55% of for the 2-, 5-, and 100-year design storms, respectively. The cost-effectiveness curves (i.e., the Pareto fronts) suggest there exists a largely linear relationship between the level of NBS implementation and TSS pollutant load reduction between the 2-year and 5-year design storms. Decision-makers can then use these results to determine optimal NBS planning according to target expenditures. The cost-effectiveness curve in **Fig.** informs which Generation and Population model provides the most efficient hydro-environmental outcomes from the ~25,000 scenarios that were simulated in SWMM. By assessing the far-right portion of the Pareto front, decision-makers may identify at which point further investment in NBS technologies yield no additional improvement in hydro-environmental goals. As such, hydrologic versus environmental efficacy goals may be compared and contrasted between scenarios as a function of cost distribution and intensity of design storm metrics (SFEI, 2020). For example, if decision-makers had a goal of reducing the 100-YR storm flow by 5% (equating to a total cost of $1,187M on the hydrologic cost-effectiveness curve), stakeholders could quickly visualize the flow reduction efficiency for additional design storms and the tradeoffs associated with pollutant load abatement at this cost point. To demonstrate how such optimization outputs may be combined with the multi-objective Gini coefficient described in **Sect. 2.4**, the 5-YR storm event with $1,000M NBS expenditure was chosen for further analysis. In this scenario, Generation 97, Population 117 produced the most optimal NBS allocation scenario according to hydro-environmental efficiency. In comparing the spatial distribution of NBSs from this model with the areas of highest social deprivation in the WOB watershed, we may note how sole reliance upon hydrological characteristics for NBS planning could result in a missed opportunity to address potential social benefits from enhanced urban greening. As such, the multi-objective Gini is explored to refine the NBS optimization results.

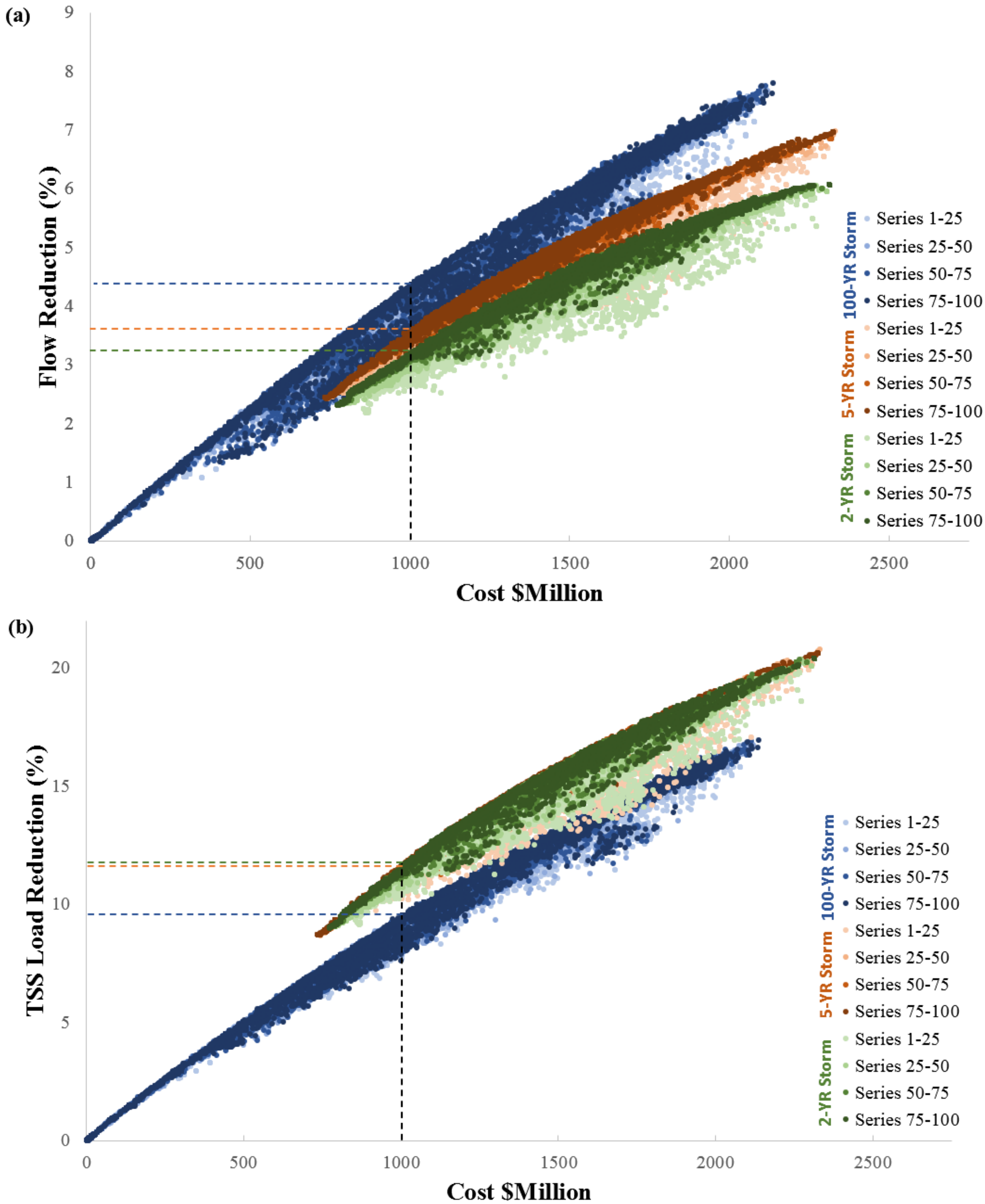

Fig. 7. GreenPlan-IT optimization output for WOB: **(a)** flow reduction as a function of cost-efficiency; **(b)** pollutant load reduction as a function of cost-efficiency.

3.2 Gini-based Optimization

A Gini coefficient less than or equal to 0.4 is commonly used as a threshold denoting fair distribution between the indicators on the x- and y-axes of the Lorenz curve (Groves-Kirkby et al., 2009; Sadras and Bongiovanni, 2004). By plotting the Lorenz curves for the SWMM-based optimization model (Generation 97, Population 117) in **Fig. 8**, the Gini coefficients according to hydrologic efficiency, pollutant load efficiency, and social equity were calculate as 0.17, 0.10, and 0.46, respectively. Such results suggest a greater equity in NBS allocation on the basis of hydro-dynamics compared with social characteristics. The large area between the Lorenz curve arc and the line of equality in **Fig. 8c** reveals poor allocation fairness corresponding to spatial distribution of neighborhood deprivation (i.e., the ADI index).

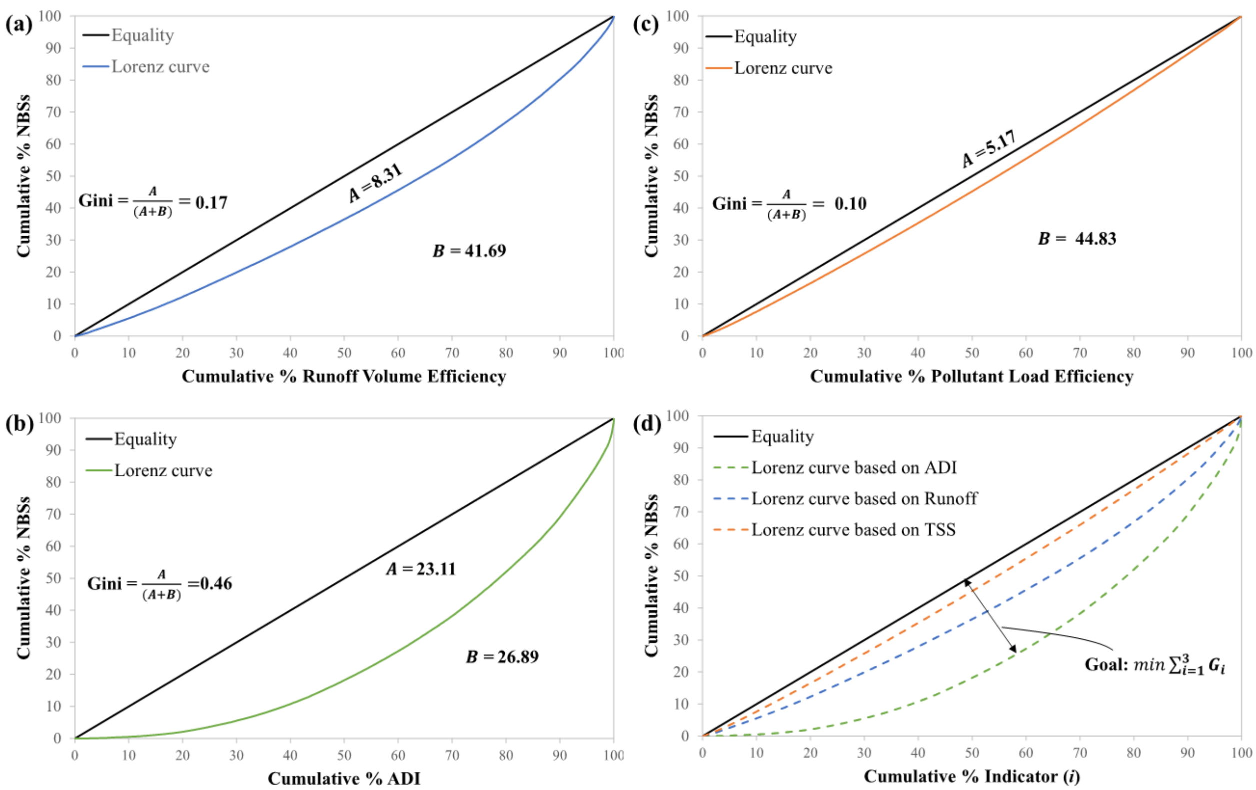

Fig. 8. Gini coefficients for Generation 97, Population 117 based on **(a)** runoff volume efficiency, **(b)** pollutant load efficiency, **(c)** Area Deprivation Index, and **(d)** cumulative indicators.

A sample set of outputs from the GreenPlan-IT tool was selected from the 5-YR storm event, each resulting in a total NBS implementation cost of ~$1,000M, to assess how the optimal allocation scheme may shift when the multi-objective Gini coefficient is applied. As shown in **Fig. 9** and summarized in **Table 1**, a series of 10 possible NBS planning scenarios were evaluated on the basis of the composite Gini coefficient for hydrologic, environmental, and social indicators. By comparing the width of the Lorenz curves and minimizing the total Gini coefficient between these scenarios, **Fig. 9** reveals that the greatest distribution of equality occurs in planning scenario Generation 22, Population 246. The ideal Gini-based scheme provides a more equal distribution of overall benefits in comparison to the optimal scenario based solely on SWMM modeling (G_i=0.67 in Generation 22, Population 246 and G_i=0.73 in Generation 97, Population 117), despite a similar investment in financial resources. The construction of a multi-objective Lorenz curve is demonstrated here as a simple plot of cumulative NBS spatial allocation against cumulative evaluation indicators, allowing for easily interpretable comparisons across planning scenarios. The area between the Lorenz curve and the diagonal is proposed as a holistic index of socio-environmental-hydrological benefits in NBS planning. A larger area below the Lorenz curve suggests that the risk of stormwater-based metrics and social-based metrics are more variable within the planning paradigm, while a smaller area under the curve indicates a more uniform distribution of spatial planning for achieving multiple objectives. The Gini index is a straightforward calculation that could be used in NBS planning to merge holistic benefits using simple algebra. Since the coefficient of derivation under the Lorenz curve is calculated as a standard deviation according to the coefficient of variation, variation is relative, and thus invariant to changes in spatial scale. In other words, the Gini index provides a transparent measurement tool of the summary of impact fractions for optimal planning (Lee, 1997).

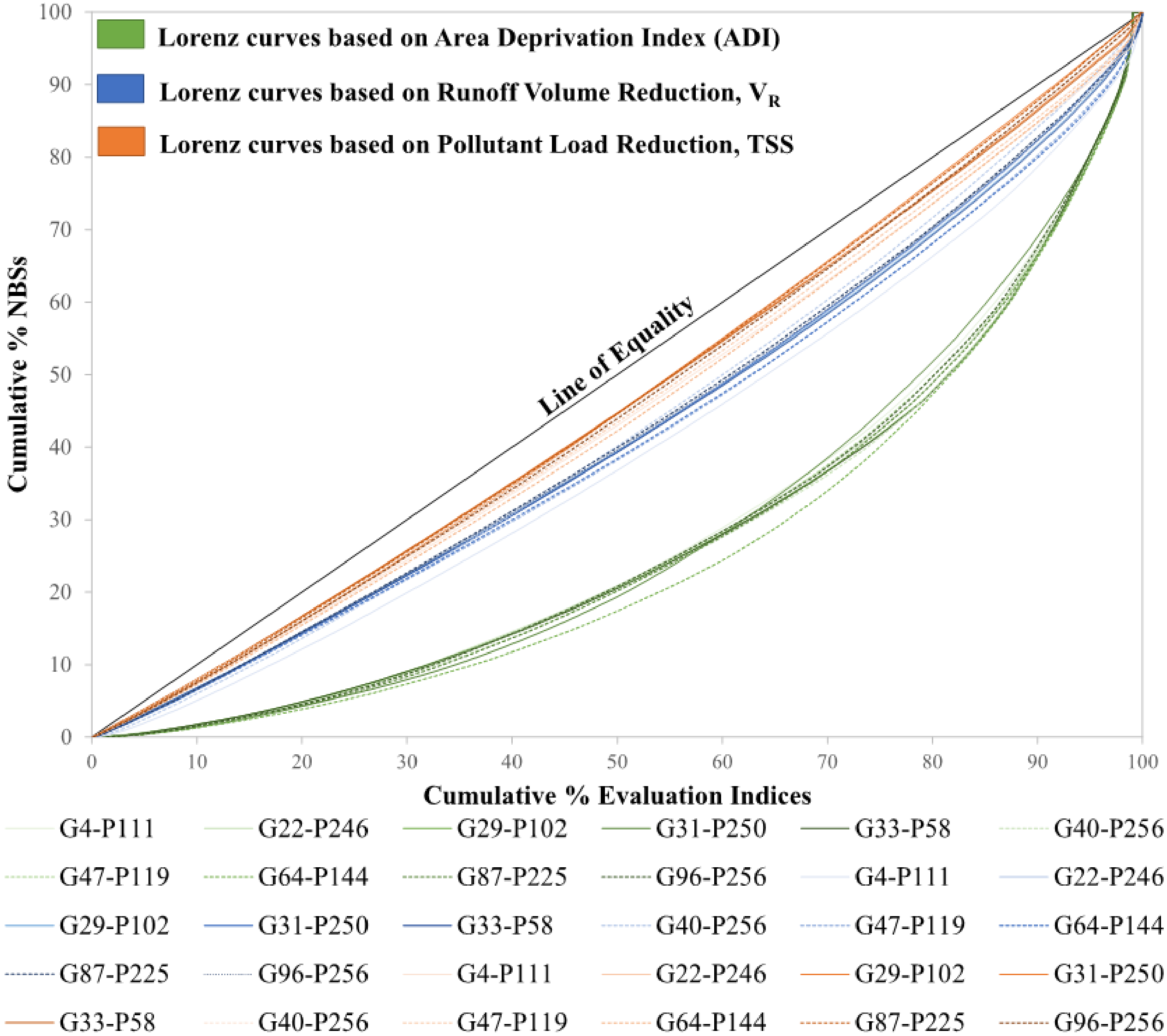

Fig. 9. Series of Lorenz curves for select 5-YR, ~$1,000M optimization models.

Table 1. Multi-objective Gini coefficients for select 5-YR storm optimization series.

Gen	**G4**	**G22**	**G29**	**G31**	**G33**	**G40**	**G47**	**G64**	**G87**	**G96**
Pop	**P111**	**P246**	**P102**	**P250**	**P58**	**P256**	**P119**	**P144**	**P225**	**P256**
G_{ADI}	0.436	0.443	0.448	0.442	0.449	0.455	0.444	0.482	0.452	0.442
G_{VR}	0.210	0.157	0.161	0.158	0.163	0.146	0.179	0.178	0.150	0.155
G_{TSS}	0.108	0.072	0.078	0.074	0.080	0.081	0.097	0.112	0.073	0.086
$\sum G_i$	0.251	0.224	0.229	0.225	0.231	0.333	0.240	0.256	0.225	0.228

The optimal allocation of NBSs throughout the planning area may now be adjusted according to the results of the composite Gini coefficient. In **Fig. 3**, the spatial distribution of NBS allocation according to SWMM-based optimization (i.e., Generation 97, Population 117, from the Pareto front curve) is compared to the spatial distribution of NBSs from the Gini-based optimization (i.e., Generation 22, Population 246, from the minimized composite G_i). By plotting the subcatchments in each scenario as a weighted proportion of NBSs to ADI deprivation, **Fig. 3d** demonstrates a higher influence of NBS area on the allocation of social equity in the Gini-based scheme, thereby promoting improved societal conditions while maintaining robust hydro-environmental efficiency. As summarized in **Table** , both allocation scenarios produce similar runoff volume and pollutant load reduction benefits for roughly the same implementation cost. However, the unique spatial allocation of the NBS features within the Gini-based scenario addresses an additional 18.48% of land areas with high neighborhood disadvantage, as measured by the ADI index.

The pattern of total allocation of benefits between the SWMM-based and the Gini-based framework is further demonstrated in **Fig. 41**, where the pie charts represent the weighted efficiency achieved in each subcatchment according to hydrologic, environmental, and social aspects. The green portions of the pie charts in **Fig. 41** reveals a greater influence of NBS allocation to ADI improvement in Generation 22, Population 246. The primary reason for this disparity is that areas highly prone to flooding or environmental quality issues are not always spatially proportional to areas of high social deprivation. As such, reliance upon a "worst-first" approach to NBS planning through the lens of hydro-dynamics may result in non-optimal allocation for addressing the many societal benefits provided by NBS solutions.

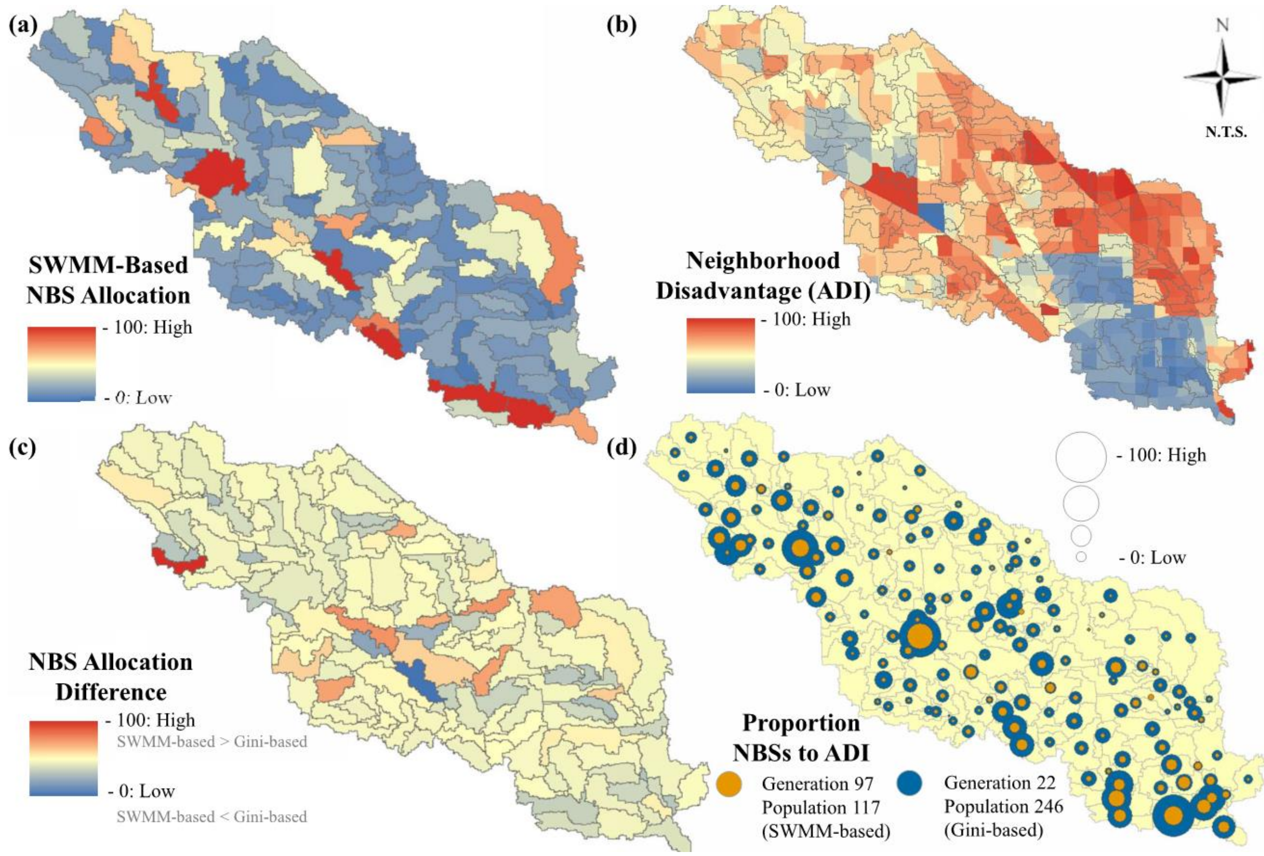

Fig. 30. Comparison of spatial distribution in the WOB watershed for **(a)** NBS allocation according to optimal hydro-environmental efficiency (Generation 97, Population 117), **(b)** areas of neighborhood disadvantage, represented by the Area Deprivation Index (ADI), **(c)** difference between NBS allocation for SWMM-based optimization (Generation 97, Population 117) versus Gini-based optimization (Generation 22, Population 246), and **(d)** weighted proportion of NBS allocation within each subcatchment compared to ADI deprivation metrics.

Table 2. Comparison of SWMM-based optimized model versus Gini-based optimized model.

	G97 P117	**G22 P246**
Cost ($M)	$1006	$1000
Runoff Volume Reduction	3.45%	3.38%
Pollutant Load Reduction	11.15%	11.28%
No. Bioretention Cells	168,459	189,385
No. Porous Pavements	8,705	7,772
No. Tree Boxes	239,001	154,824
% ADI Addressed by NBSs	16.84%	35.32%

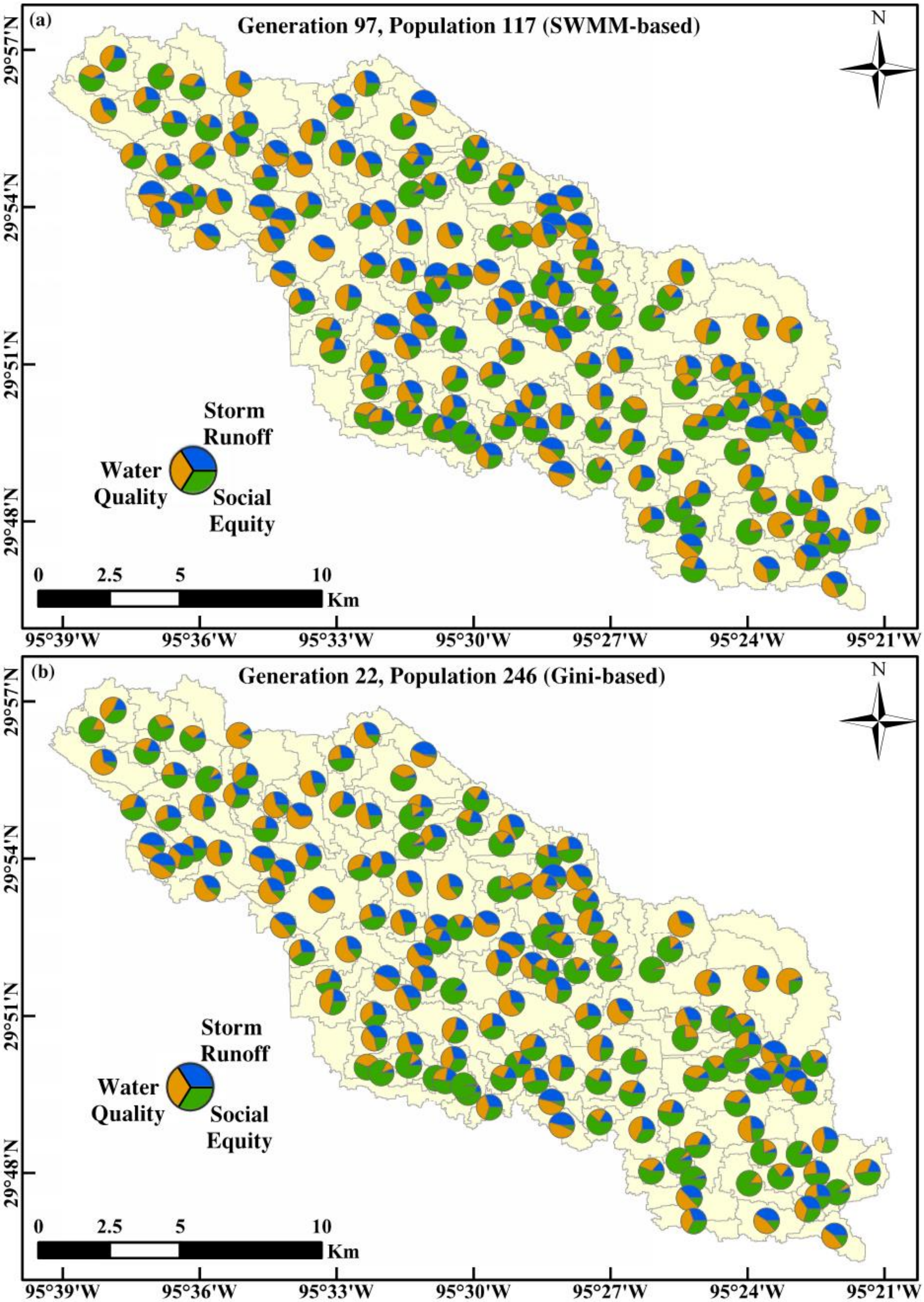

Fig. 41. Proportional representation of evaluation indicator efficiency for **(a)** SWMM-based optimization model, and **(b)** Gini-based optimization model.

4 Conclusion

NBS design is a function of rapid urban development, quality of life goals, and a scarcity of resources for addressing hydro-meteorological challenges. As such, proper co-development of NBS plans can and should account for the multi-functional components involved in all of these processes, and we must do so in a coherent fashion for optimal impact in the coming era of water science. While coupled social and physical models have proliferated within the general realm of water security (e.g., droughts, water use, hydro-meteorological hazards, migration, agriculture, etc.), the foundation of such a framework has been hitherto lacking within the NBS scientific literature. In considering the rising popularity of urban green infrastructure, we are presented with an opportunity to re-cast how decision-making operates in order to maximize the numerous co-benefits associated with NBSs. As resilience and sustainability goals have become increasingly linked, many governmental agencies are seeking the prioritization of NBS capital improvement projects using an equity-based or benefits-based prioritization metric to help guide holistic investments rather than focusing in a one dimensional benefit (Marchese et al., 2018).

In this light, strategic NBS planning requires real-world empirical datasets (e.g., social vulnerability, watershed properties) and actionable frameworks (e.g., equity-based planning) to aid in optimal planning amongst disparate social and physical domains (Frantzeskaki, McPhearson, Collier, et al., 2019). When we are better able to select the optimal location of NBSs at the watershed-scale, the specific typologies and precise placement may be analyzed using the numerous platforms that currently operate through small-scale physical modeling (e.g., EPA's SWMM). To date, there has been very little research on NBS optimization at the watershed-scale and even less progress in combining numerical modeling with comprehensive social benefits and human impacts. As we continue to have increased access to heterogenous datasets, novel frameworks that leverage the strengths of geospatial properties will enhance our understanding of diverse co-benefits to answer challenging questions associated with multi-functional planning.

As such, we demonstrated here how real-world social and hydro-environmental complexities may be amalgamated using a novel application of the area Gini coefficient for actionable science. The White Oak Bayou case study investigated how social equity and watershed dynamics propagate throughout the NBS system, which is fundamental to planning for an equitable environment. This study harmonized multi-indicator planning by facilitating an explicit integration of social determinants within the framework of natural-planning using data-driven science. This research transitioned beyond the standard focus of watershed physiological characteristics to investigate the complex associations relating social patterns and watershed efficacy.

The practical implications of this study will enhance the user-friendliness of NBS spatial planning in a flexible manner while merging well-established hydrological methodologies with social co-benefits (Kuller et al., 2017). When we are better able to connect the dots between social constructs, environmental processes, and the hydrological cycle, which are all complex processes that operate cohesively amongst one another, we can establish optimal patterns within the seemingly chaotic network of NBS sub-processes. By constructing models with inter-disciplinary elements, the foundation for novel research regarding how NBSs function in diverse geographical locations is strengthened. In a world with increasing socio-environmental stressors and finite resources, this research will improve public policy interventions by providing the knowledge necessary for identifying, quantifying, and linking complex interactions of NBS functions for sound decision-making.

Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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SUPPLEMENTARY MATERIAL

Optimal planning of natural stormwater solutions using a composite Gini coefficient: A watershed assessment of hydrological, environmental, social, and economic efficiency

Cyndi V. Castro

Contents of this file:

Table S.1. Atlas 14 rainfall coefficients for Houston, Texas, USA.

Rainfall Frequency	b (inches)	d (minutes)	e
2-Year (50% AEP)	47.25	8.94	0.7263
5-Year (20% AEP)	54.09	8.34	0.7051
10-Year (10% AEP)	55.26	7.30	0.6752
25-Year (4% AEP)	56.72	6.12	0.6397
50-Year (2% AEP)	57.94	5.47	0.6166
100-Year (1% AEP)	56.68	4.46	0.5857

Table S.2. Pollutant load parameters for modeling total suspended solids (TSS).

		Removal Efficiency (%)		
Land Use	**TSS** *(mg/L)*	*Porous Pavement*	*Bioretention Cell*	*Tree Box*
Industrial	145.43			
Residential	146.00			
Mixed Use	72.93	60%	50%	50%
Commercial	92.56			
Open Space	211.33			

Table S.3. Water balance zones represented in the WOB case study.

NBS Feature	Surface	Soil	Storage	Underdrain
Porous Pavement	X		X	X
Bioretention Cell	X	X	X	X
Tree Box	X	X	X	

Table S.4. PCSWMM LID Control Editor parameter inputs. BIOR: “Bioretention cell”, PMPV: “Permeable pavement”, TRBX: “Tree box”.

	Parameter	NBS Feature			Units
		BIOR	PMPV	TRBX	
Surface	Berm height	9	0	12	Inch
	Vegetation volume	0	0	0.2	Fraction
	Surface roughness	0.1	0.1	0.1	-
	Surface slope	1.0	1.0	1.0	Percent
Pavement	Thickness	-	4	-	Inch
	Void ratio	-	0.15	-	Voids/solids
	Impervious surface	-	0	-	Fraction
	Permeability	-	100	-	Inch/hour
Soil	Thickness	18	0	21	Inch
	Porosity	0.5	0.5	0.5	Volume fraction
	Field capacity	0.2	0.2	0.2	Volume fraction
	Wilting point	0.1	0.1	0.1	Volume fraction
	Conductivity	5	0.5	50	Inch/hour
	Conductivity slope	10	10	10	-
	Suction head	3.5	3.5	3.5	Inch
Storage	Thickness	12	24	6	Inch
	Void ratio	0.75	0.75	0.75	Voids/solids
	Seepage rate	0.5	5	0.5	Inch/hour
	Clogging factor	0	0	0	-
Drain	Drain coefficient	5	100	50	Inch/hour
	Drain exponent	0.5	0.5	0.5	-
	Drain offset height	12	8	0	Inch

Table S.5. ISE statistics between simulated and observed flows for calibration.

		Gauge No. 08074500	Gauge No. 08074020
Storm Event No.	Date	Rating (ISE)	
1	Nov. 27, 2020	Good (8.4)	Good (6.3)
2	Dec. 2, 2020	Good (8.9)	Good (10.0)
3	Dec. 11, 2020	Good (9.3)	Fair (11.3)
4	Dec. 13, 2020	Fair (13.7)	Good (6.3)
5	Dec. 19, 2020	Very Good (5.9)	Good (8.3)
6	Dec. 30, 2020	Good (10.0)	Very Good (6.0)
7	Jan. 6, 2021	Good (10.7)	Fair (11.0)
8	Jan. 10, 2021	Good (7.2)	Good (7.5)
9	Feb. 11, 2021	Good (8.3)	Good (7.5)
10	Feb. 17, 2021	Very Good (4.6)	Good (7.1)

Table S.6. ISE statistics between simulated and observed flows for validation.

		Gauge No. 08074500	Gauge No. 08074020
Storm Event No.	Date	Rating (ISE)	
1	Apr. 30, 2021	Very Good (4.7)	Very Good (5.9)
2	May 16, 2021	Very Good (5.9)	Very Good (5.9)
3	May 22, 2021	Very Good (4.8)	Very Good (4.9)
4	Jun. 2, 2021	Good (6.8)	Good (7.6)
5	Jun. 27, 2021	Good (8.8)	Very Good (4.6)
6	Jul. 3, 2021	Very Good (4.5)	Very Good (4.9)
7	Jul. 8, 2021	Very Good (5.2)	Good (9.0)
8	Jul. 15, 2021	Very Good (5.6)	Good (6.4)

Table S.7. GreenPlan-IT Optimization Tool subcatchment input file. BIOR: "Bioretention cell", PMPV: "Permeable pavement", TRBX: "Tree box".

			No. Possible NBS Features		
Subcatchment No.	**Area (AC)**	**Impervious Cover (%)**	**BIOR**	**PMPV**	**TRBX**
1	709.4	43.7	4904	96	7761
2	1420.5	45.4	18158	317	17632
3	683	40.7	8178	37	10573
4	363.1	47.6	1449	43	9745
5	588.5	33.5	6639	229	214
6	358.6	51.5	1815	4	9404
7	712	32.5	17376	93	3208
8	815	46.5	12339	362	4034
9	913	43.7	11430	157	14351
10	432.8	40.9	4932	96	387
11	584.9	52	4521	133	9299
12	62.4	32.6	1385	4	22
13	86.7	47.8	937	0	1984
14	1018.4	34.8	7250	192	11130
15	519.2	50.7	6103	194	8295
16	358.4	33.9	4273	38	3359
17	270.7	54.7	1537	35	8309
18	256.3	59	680	17	10540
19	871.2	59	6796	333	12400
20	300.7	24.7	1780	123	259
21	197.7	59.1	1602	195	231
22	399.5	64.3	3392	313	5719
23	519	31.4	8859	55	0
24	382.5	42.9	3635	183	547
25	226.8	52.6	1843	18	3654
26	447.7	41.8	6841	87	643
27	502.9	59.5	5273	217	7760
28	358.4	39.2	3186	143	168
29	282.3	20.1	4122	10	0
30	614.4	41.7	6045	7	4934
31	42.5	65.9	284	69	154
32	153.3	31.6	3360	0	1519
33	340.4	51.1	6349	341	131
34	83.4	62.3	1074	63	145
35	261.7	44	1175	7	488

Table S.7 (continued):

			No. Possible NBS Features		
Subcatchment No.	**Area (AC)**	**Impervious Cover (%)**	**BIOR**	**PMPV**	**TRBX**
36	458.3	54.5	3629	44	11804
37	966.4	51.6	12159	287	9376
38	279.7	43.4	1746	87	968
39	1004	37.3	5286	31	1553
40	47	28.4	1330	0	105
41	480.7	43.8	6856	215	857
42	169.6	38.6	2098	0	4163
43	391	31.5	1486	13	1441
44	341.4	51.6	5228	174	157
45	413.6	43.5	4583	31	1472
46	69.5	18.6	1041	0	339
47	467.3	49.7	4184	311	302
48	1197.9	51.8	11504	399	16692
49	590.3	52.2	4907	96	14166
50	250.2	53.9	1181	88	6201
51	562	41.4	5508	23	12750
52	549.5	42.9	4888	28	11791
53	312.8	57.8	1122	14	10247
54	333.8	38.6	5519	51	884
55	108.4	39.6	1592	77	0
56	431.6	41.5	4998	8	8551
57	349.6	22.6	3603	30	1829
58	712.5	43.2	5598	60	11214
59	96.6	37.1	1051	0	2461
60	35.2	54.9	443	0	64
61	358.6	37.3	3386	24	6237
62	318.4	63.7	3010	343	866
63	61.4	42.8	352	0	909
64	302.1	42.1	1288	32	2621
65	811.4	47.7	6421	248	6760
66	182.1	49.6	2088	121	2277
67	0.7	13.8	25	0	0
68	326.9	49.4	1317	29	3681
69	1903.1	55.1	13296	1533	18592
70	171.7	61.5	1461	135	1313
71	1017	29.8	21837	97	6886

Table S.7 (continued):

			No. Possible NBS Features		
Subcatchment No.	**Area (AC)**	**Impervious Cover (%)**	**BIOR**	**PMPV**	**TRBX**
73	501.5	39.8	6885	29	3604
74	909.5	55.3	13125	525	3490
75	237.6	73	1157	241	52
76	596.7	51.5	8741	299	2639
77	275.4	40.3	2623	12	3336
78	1023.3	52.4	8928	816	9392
79	404.2	59.7	3704	442	3597
80	93.8	48.5	542	36	376
81	163.5	73.3	534	164	1366
82	1398	62.6	6316	1408	15463
83	314.7	55.6	3722	141	1979
84	123.5	34.2	1365	4	828
85	551.8	49.5	4846	335	2798
86	388.8	32.5	5615	7	2605
87	564.6	40	6756	103	2275
88	1.2	58.9	14	0	11
89	1190.6	55.6	7910	463	18147
90	489.7	65.1	3051	472	4521
91	634.5	40.4	5931	143	2033
92	293.6	54.7	3685	215	233
93	814.7	67.1	3245	915	6251
94	407.7	38.4	6199	48	5144
95	448.8	59.3	2304	301	2699
96	484.7	35.2	11246	123	2632
97	142.4	43.8	1735	27	915
98	317.7	47.5	2468	87	6240
99	488.3	62.1	4068	354	5290
100	219.5	48.7	1717	80	2722
101	375.6	61	4213	207	2548
102	627.4	47.2	3638	141	8215
103	185.9	44.6	1712	23	2889
105	103.5	54.8	913	61	701
106	90.2	59	339	19	1367
107	604.3	51	2368	221	12431
108	947.3	55	5377	183	18362
109	589.4	46.3	2149	195	6186

Table S.7 (continued):

Subcatchment No.	Area (AC)	Impervious Cover (%)	No. Possible NBS Features		
			BIOR	**PMPV**	**TRBX**
111	339.2	68.4	1326	371	2715
112	236.7	61.1	621	115	7151
113	45.8	72.1	72	68	339
114	518.8	53.8	2244	150	12494
116	278.7	47.1	1650	42	3050
117	11.1	44.5	18	0	26
118	350.3	55.5	1165	186	4659
119	413.9	38.5	6706	26	4730
120	150.9	64.9	572	207	2181
121	264.1	43.1	1289	101	1848
123	144.6	56	528	98	984
124	383.9	56.2	2068	186	3162
125	252.5	60.8	637	141	4223
126	10.6	47.9	7	0	0
127	24.6	72.9	50	52	57
128	489	48.5	1604	91	2793
129	258	59	403	159	2750
130	367.1	58.1	1306	232	2556
131	6.4	53.2	11	0	119
132	284.7	60.3	765	233	3487
133	314.7	60.6	532	155	3444
134	296.5	63.3	1974	206	1981
135	484.7	51.3	1866	255	4755
136	335.2	80.9	486	687	3635
137	1051.4	63.4	2509	880	16024
138	753.6	56.7	2267	471	10215
139	448.8	80.6	617	921	3912
140	721.4	57.3	2162	329	11066
141	291.7	59.4	1007	126	2480
143	263.4	64.1	824	212	4076
144	747.2	68.3	345	698	23024
145	725.4	60.9	1298	395	15412
146	247.3	47.2	1255	23	5297
147	38.5	43	307	6	478
148	411.3	65.1	81	110	16841
149	147.6	68.7	107	96	4682

Table S.7 (continued):

Subcatchment No.	Area (AC)	Impervious Cover (%)	No. Possible NBS Features		
			BIOR	PMPV	TRBX
151	392.6	65.1	154	61	17508
152	379.4	55.9	916	171	9809
153	10.9	33.6	114	0	225
154	540.7	68.2	1114	314	10807
155	820.9	64.3	3071	998	12983
156	593.4	60.4	223	37	23936
157	94.3	56.3	596	13	2427
158	218	56.1	874	23	8214
159	177.2	55.1	982	62	4267
160	660.5	64.6	2867	750	13880
161	483.1	69	1038	559	8147
162	486.4	70.5	590	395	11047

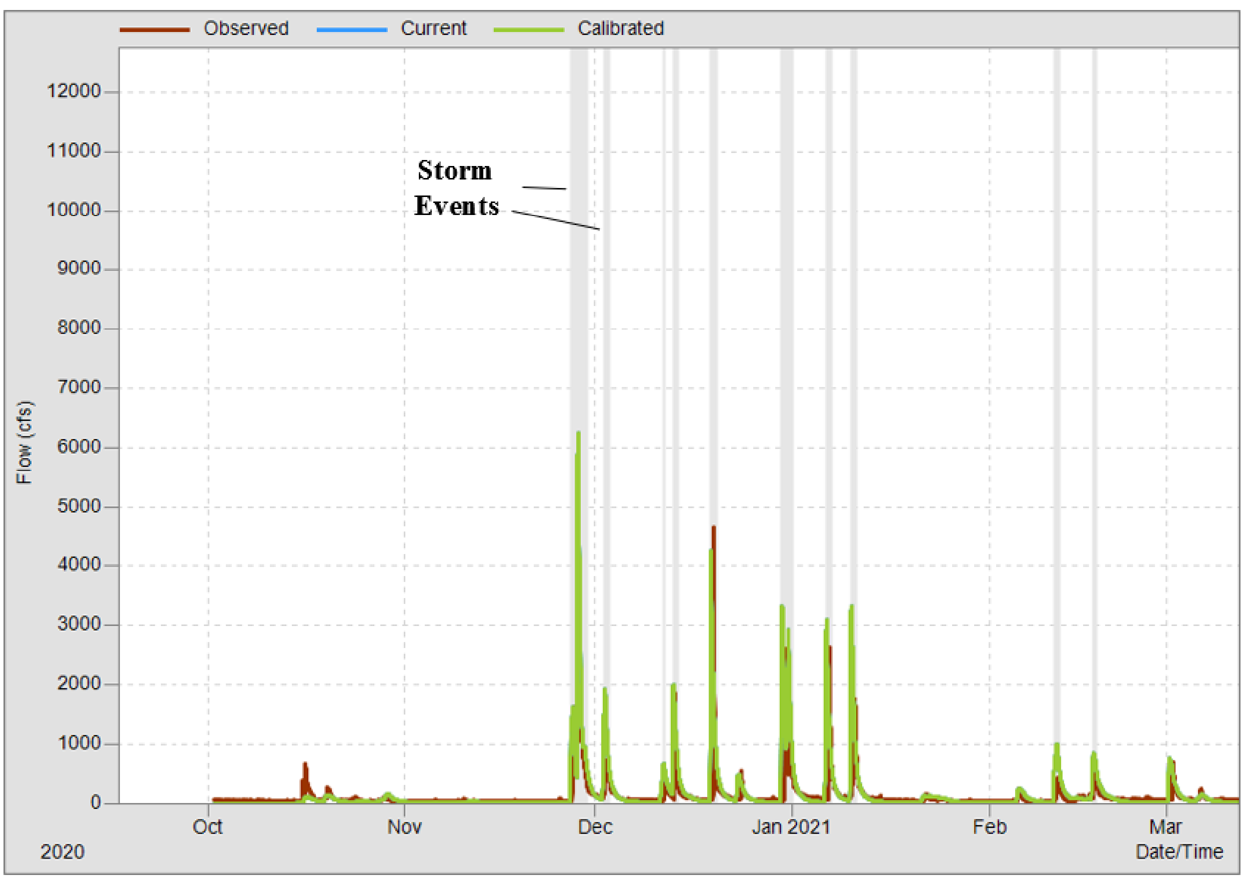

Fig. S.1. Sample of storm event selection in PCSWMM.

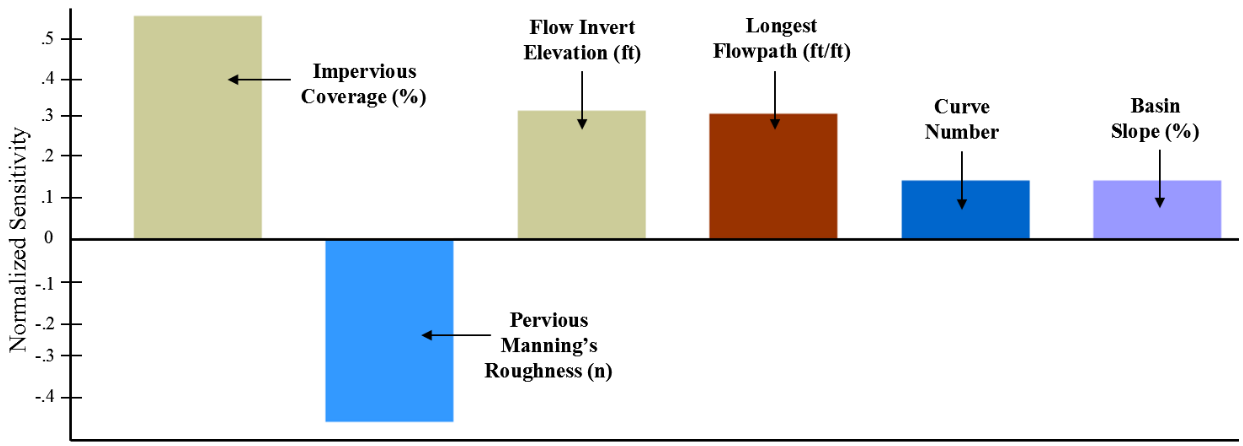

Fig. S.2. Normalized sensitivity analysis output for primary variables.

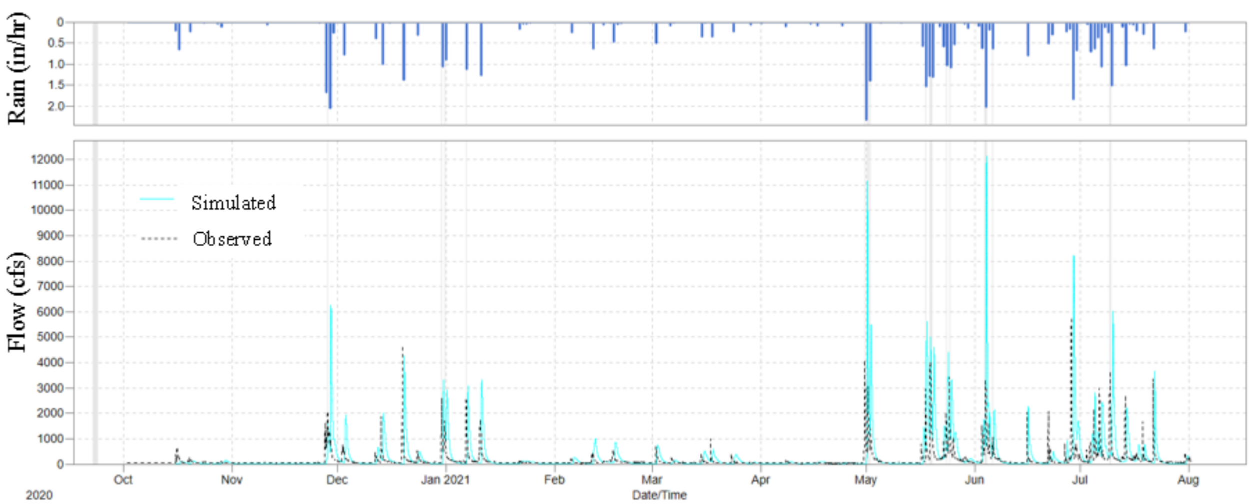

Fig. S.3. Calibration output hydrographs for USGS Gauge No. 08074500.