Coalitional Game Theory for Stormwater Management and Green Infrastructure Practices

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Abstract: As global warming and climate variability bring about more frequent and intense rainstorms and accelerate sea level rise, our social and built environments are at heightened risk of flood-induced damages and costs. All levels of governance stand to benefit from deepened understanding of possible outcomes resulting from decentralized human behavior in the realm of water resources engineering and management, particularly in coastal areas. Game theory allows scientists to predict preferred strategies and interactions of rational self-interested actors in coalitional games, wherein players increase their individual payoffs through formation of strategic subsets. When applied to infrastructure planning, this practice can be used to identify which coalitions should form to benefit their overall hydrologic system. This research aims to inform green infrastructure decisions in Charleston, South Carolina's Market Street watershed using a coalitional game theory solution concept, the Shapley value, in combination with rainfall-runoff simulation in storm water management model (SWMM). Results offer insights into stormwater services and flood managers concerning suggested areas of focus for green infrastructure spending and advocacy to reduce flooding and resulting property damage. **DOI: 10.1061/JWRMD5.WRENG-5979.**

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Introduction

Climate change has impacted human and natural systems, globally, at every level of development. Changes in the hydrological cycle observed due to global warming over the last several decades include increased atmospheric water vapor content, altered precipitation patterns, intensity and extremes, and changes in soil moisture (Bates et al. 2008). The United States has experienced an increasing percentage of intense single-day rain events between 1901 and 2014, and total annual precipitation has increased by 0.5% per decade across all 48 contiguous states and 0.2% per decade over land areas worldwide (EPA 2014). Much of our existing and aging water infrastructure is strained by these changes. However, design approaches are still based on historical hydrological events and stationarity assumptions (Bates et al. 2008; Milly et al. 2008; Goharian et al. 2016; US Global Change Research Program 2017). The consequent costs of heightened temperatures and rising seas have not distributed their risks evenly and will continue to disproportionately affect built and environmental systems in coastal areas.

The combined and exacerbated impacts of more intense storms and sea level rise (SLR) are particularly detrimental to coastal communities, threatening outdoor recreation reliant on natural systems as well as regional economies based on agriculture, fishing, and tourism (EPA 2014; US Global Change Research Program 2017). Increasing global temperatures impact sea level, storm surge, high tides, and coastal erosion, and incite loss of crucial wetland areas, which collectively impose additional natural disasters (NOAA 2022). Experts' concern with these issues would be less extreme if it were not for the human propensity to settle around bodies of water; coastal areas constitute less than 10% of the land in the contiguous United States, but house nearly 40% of the country's population (NOAA 2021). With an existing trillion-dollar coastal property market and many forms of public infrastructure at stake, high tide flooding is expected to continue to affect homes and businesses in these densely populated areas by overloading stormwater and wastewater systems while stressing surrounding estuarine ecosystems (NOAA 2022; US Global Change Research Program 2017). As population growth, economic development, and urbanization are expected to continue and compound existing coastal community vulnerability, it is imperative that adaptation and infrastructure decisions are considered in the context of long-term sustainable development (IPCC 2014).

As climate variations and land use changes continue to alter existing hydrologic conditions, additional stormwater infrastructure will be needed to reduce excess runoff and aid existing infrastructure that may not be equipped to handle these changes. Low-impact development (LID) strategies, which fall under the umbrella term of green infrastructure (GI), work in tandem with, reduce stress on, and expand the capacity of existing stormwater infrastructure by intercepting rainfall before it reaches urban drainage systems (Ahern 2011) by deterring excess rainfall from common collection points through creation, restoration, and preservation of green spaces and natural landscape features (Ellis et al. 2014; EPA 2018). A vast body of research explores the effectiveness of GI for urban runoff rate and volume reduction, be it through rainwater harvesting (Ahiablame et al. 2013; Jones and Hunt 2010; Goharian and Burian 2018), permeable pavements (Randall et al. 2020; Støvring et al. 2018; Zhang and Guo 2014), bioretention cells (Davis 2008; Wang et al. 2019), or green roofing (Bliss et al. 2009;

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William et al. 2016). Most are easily accessible to homeowners and businesses and are relatively affordable—specifically, means of rainwater harvesting and bioretention in the form of rain gardens. Additionally, GI provides an opportunity to add both aesthetic (Tupper 2012) and monetary (Ichihara and Cohen 2010; Voicu and Been 2008) value to outdoor spaces and properties. For these reasons, and their ability to bolster the capabilities of existing and aged gray infrastructure, LID strategies have a high potential to increase flood resilience in urban coastal communities. However, choices about spending and placement remain a complex water resources management problem.

Water Resources Management and Human Behavior Modeling

Increased flood frequency and associated risks affect decision making by individuals and businesses as well as water resources planners and managers. Planners must collaborate with numerous community institutions while ensuring that decisions take into consideration long-term impacts on future generations and fit into budget constraints, as well as limited developed and urban spaces (Ahern 2011; Loucks and van Beek 2017). There are plentiful studies that have aimed to inform LID placement and design decisions using rainfall-runoff simulations in the EPA's Stormwater Management Model (SWMM) (Bai et al. 2018; Kim et al. 2018; Qin et al. 2013; Simpson 2010; York et al. 2015; Zahmatkesh et al. 2014) as well as a variety of studies that have coupled SWMM simulations with optimization algorithms (Eckart et al. 2018; Ghodsi et al. 2020; Macro et al. 2019; Raei et al. 2019; Xu et al. 2017). This category of study is suitable for informing centralized decision-making surrounding GI but neglects the drivers of and human behaviors behind decentralized GI decisions.

LIDs are a decentralized form of infrastructure, able to be installed by individual property owners with or without financial incentives from governing bodies. This accessibility is a trade-off for smaller service areas, and so widespread adoption through community participation is needed in order to see systemwide benefits (Ahiablame and Shakya 2016; Baptiste et al. 2015; Montalto et al. 2013; Ureta et al. 2021). Multiple studies have attempted to identify community barriers to GI participation, with findings ranging from household characteristics (Ureta et al. 2021), lack of public understanding about individual roles in stormwater management (Chaffin et al. 2016), lack of trust and communication between stakeholder groups (Van De Meene et al. 2009), property restrictions (Coleman et al. 2018), and lack of direct financial incentives (Carter and Fowler 2008).

A combination of beliefs and barriers across communities work together to produce system-wide collective and emergent behavior. agent-based modeling (ABM) methods offer a means of simulating these diverse behaviors, relationships, and interactions among individuals, or actors, within their environment (Macal and North 2010). Applications for water resources management are still relatively limited (Berglund 2015), but ABM has the potential to allow modelers to observe, plan for, and understand the long- and short-term outcomes of ecological, environmental, economic, and social changes, which are all-important aspects of the water resource system planning and management (Loucks and van Beek 2017). ABM has been used to investigate possible outcomes and emergent responses to various climate, policy, flood, and subsidy scenarios (An et al. 2005; Manson 2001; Parker et al. 2003), some coupled with hydraulic models (Abebe et al. 2019a, b, 2020; Dawson et al. 2011; Hyun et al. 2019; Michaelis et al. 2020). While ABMs are particularly suited to the study of local-global interactions, effects of heterogeneity on emergence, and decentralized decision-making (Bandini et al. 2009), Data are lacking on agents themselves, limiting reliability of parametrized human behaviors (Macal and North 2010; Michaelis et al. 2020; Patt and Siebenhüner 2005; Yang et al. 2018). Extensive data collection requirements and challenges in modeling both communications and complex interactions among individuals make this method of study a nontrivial task (Niazi and Hussain 2012) for water management researchers.

Game theory analysis, not yet implemented to a great extent in water resources management, allows for the prediction of human behavior in response to conflict and omits the need for behavioral data as well as the modeling challenges presented by ABM methods (Madani 2010; Parrachino et al. 2006). Predicted game theory outcomes often differ from those found using traditional optimization methods, as they take into consideration and prioritize individual stakeholder objectives rather than system objectives, and allow modelers to observe how individual goals affect system outcomes and evolution (Madani 2010). Game theory can incorporate decision makers' potential actions, preferences, and strategic choices in the face of conflict, allowing researchers to predict individual decisions in differing scenarios, give advice to relevant parties, and inform future (Farooqui and Niazi 2016) planning, policy, and design conflicts (Madani 2010). Cooperative game theory (CGT), in which agents work together and bargain with one another, offers solutions to allocation problems that can serve as a basis for, for example, agreements among parties dealing with cost-sharing conflicts or benefits allocation following player cooperation (Myerson 1991). Applications of CGT in water resources dilemmas include allocation of maintenance costs for a shared irrigation system (Miquel et al. 2006), electricity and production cost from shared hydroelectric power (Gately 1974), pollution allowance (Kilgour et al. 1988), aquifer resources (Just and Netanyahu 2004), and water rights (Braden et al. 1991). However, the use of game theory to consider the socioeconomic impacts of flood management and stormwater management practice has not been well-established.

William et al. (2017) used a CGT solution concept, the Shapley value, to investigate the impacts of various stormwater management policies in incentivizing GI implementation for community participation in bioretention cell installation in an urban watershed. Results provide insights concerning spatial bargaining power in the study area, with analysis revealing which subbasins are adequately reimbursed in terms of decreased stormwater pollutant loads versus the expenses they incur for GI installation. Still, there are no studies, to the authors' knowledge, that leverage CGT concepts in this manner to inform cost-effective LID placement for the purpose of stormwater capture and local flood damage reduction.

Heavier precipitation events, SLR, and increasingly severe storm surge are expected to cause lasting damage to existing coastal properties and infrastructure. Aging traditional stormwater infrastructure in these areas is not expected to be able to adequately handle these changes and would benefit from increased capacity by way of widespread GI installation. Additionally, planners, governing bodies, and relevant stakeholders would benefit from further knowledge surrounding increasing community participation in stormwater management efforts, as well as means of informed predictions for where LID projects will be most beneficial and cost-effective in the long term. For this reason, this research proposes the use of CGT analysis to inform LID placement, spending, and GI advocacy focus on coastal Charleston, South Carolina. Additionally, this study explores the potential of community-wide individual GI installation efforts to reduce system-level damage in the face of large-scale flood events. Results provide insights into spatial flood damage and flood reduction benefits as well as study subarea bargaining power, with analysis revealing areas in Charleston that would be adequately reimbursed in terms of decreased flooding and economic damage for the cost incurred for multiple GI installation scenarios.

Case Study

The City of Charleston, South Carolina, is a major port along the southeastern coast of the United States situated on an inlet of the Atlantic Ocean formed by the confluence of the Ashley and Cooper Rivers (Charleston County 2010). The city is an economic engine for the state by way of both trade and manufacturing, but the core of its revenue is reliant on an enduring heritage tourism industry (Morris and Renken 2020; Platt 2020). However, having experienced drainage and flooding problems since the city's founding (City of Charleston 2015), SLR and increased flooding events are significant threats to both Charleston's lucrative tourism economy and business community (Williams and Moore 2020).

Nuisance flooding has increased due to the compounding effects of SLR, land subsidence, and urban development, and is worsening due to ongoing population growth and approval for additional development projects (Morris and Renken 2020). The city experienced an all-time record of 89 tidal floods in 2019, translating to a flood event nearly every five days, following a previous record of 58 events in 2015 (Peterson and Porter 2020). These sunny-day flood events overwhelm the city's aging stormwater drainage system, some of which dates to the 1800s, and tidally influenced outfalls leave little capacity for contending with precipitation. In response, the city has put forth the Charleston Rainproof Program (City of Charleston 2023), which is working to educate and encourage both residents and businesses to utilize public and private spaces for rainfall capture. In the past, this program offered how-to guides and mini-grants to individuals who installed rain gardens and advertised an annual rain barrel sale. The state of South Carolina has no restrictions on rainwater harvesting, and actively encourages public participation in stormwater management.

Coastal environments, along with their inherent engineering challenges—high and tidally influenced groundwater tables, flat terrain, and poorly draining soils—experience higher than average rainfall and are particularly vulnerable to storm surges tropical storms, hurricanes, and other coastal hazards. The Spatial Hazard Events and Losses Database for the United States (SHELDUS) reported an aggregated property damage cost of nearly \$54 billion for Charleston County between 2000 and 2019, nearly 85% of which was reportedly caused by hurricane, tropical storm, and flooding events, even though these categories accounted for only 32% of the total hazard events experienced in that time frame (CEMHS 2020). One of these events was the historic South Carolina flood, also referred to as the infamous "1,000-year flood," which occurred over the course of five days in the fall of 2015 (City of Charleston 2015; Weather Underground 2015). Widespread, heavy rainfall flooded central and coastal areas of the state, with many locations recording rainfall rates of 2 in./h, costing an estimated \$1.5 billion in damages (NOAA 2016). The City of Charleston experienced both extreme rainfall and tide elevations and was hit with a record-breaking 11.5 inches of rain in 24 h on October 3, and more than 23 inches of rain over the course of the whole event (City of Charleston 2015; Weather Underground 2015). The 1,000-year flood serves as the case study for investigating the ability of widespread, decentralized GI installation to reduce flood damage costs in urban coastal environments.

Methods

Model Development in PCSWMM

The study area was limited to the Market Street watershed, an area in Charleston's Old Historic District that experiences high tourist visitation and frequent nuisance flooding. To analyze GI and rainfall-runoff interactions during the historic South Carolina flood, a one-dimensional model representing rainfall, runoff, evaporation, and infiltration was developed in PCSWMM in accordance with requirements and suggestions in the SWMM user's manual version 5.1 (EPA and Rossman 2015). This model and many of its inputs were derived from a previously developed PCSWMM rainfall-runoff model of the Charleston Peninsula. Input sources and data preparation concerning the watershed boundary, infiltration and overland flow parameters, depression storage, land cover, impervious area, and land elevation are detailed in Lawyer (2022).

The model uses a 15-min time step for the total 120-h duration, beginning at time 0:00:00 October 1, 2015, and ending at 0:00:00 October 6, 2015. Daily evaporation depth values were input in PCSWMM for the duration of the storm event (Climate Engine 2021). Rainfall data were obtained in the form of hourly precipitation for the specified simulation date range from the Charleston International Airport Station (Weather Underground 2015) (Fig. 1). Corresponding water level data were obtained from the Charleston Cooper River Entrance Station and assigned to each of the peninsula basins' outfalls to account for backwater flows when applicable (NOAA 2015).

Specifications for conduit location, sizing, shape, direction of flow, and material were sourced from a hand-drawn account of Charleston's existing drainage system (Howe 1950), and were used to replicate present conditions in PCSWMM to the fullest extent possible. Ponding at junctions was not considered, and outfalls were placed according to their location on the drainage map and assumed to empty into the peninsula's surrounding water bodies.

The Market Street basin was divided into five hypothetical subbasins to create the multiple players needed for CGT analysis (Fig. 2). The divisions were based on the location of Market Street itself as well as available zoning information (City of Charleston Information and Technology GIS Division 2021a, b, c). All buildings within the subbasins were given either Residential or Commercial identifiers (Fig. 2). All Residential buildings were assumed to be single-family households. The terms "Residential" and "Household," as well as "Commercial" and "Business," are used interchangeably henceforth.

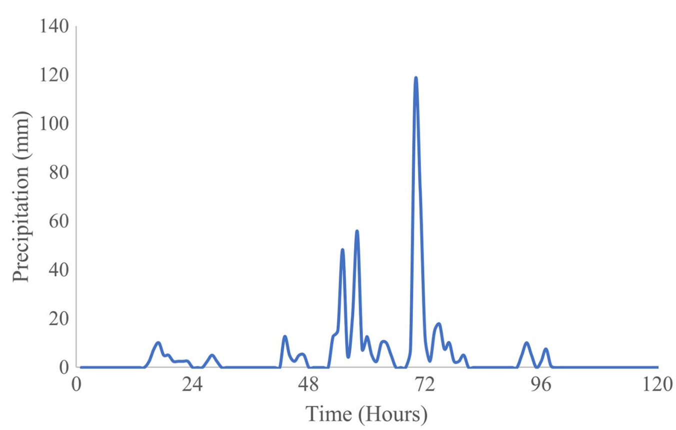

Fig. 1. 2015 Historic South Carolina flood hourly precipitation. (Data from Weather Underground 2015.)

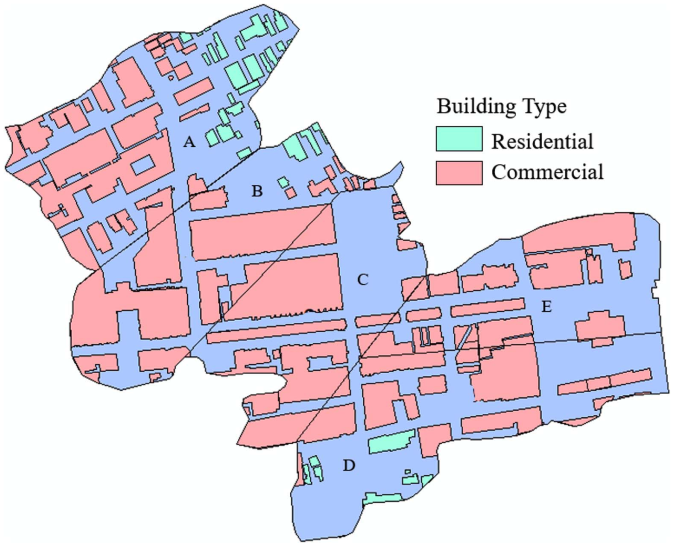

Fig. 2. Subbasin residential and commercial buildings. (Data from City of Charleston Information and Technology GIS Division 2021a.)

Coalitional Game Theory and Shapley Value

Game theory (Von Neumann and Morgenstern 1944) is a means of decision analysis that allows us to model conflict, cooperation, and communication between two or more individuals whose decisions affect each other's welfare (Farooqui and Niazi 2016; Myerson 1991). Any situation involving two or more players can be classified as a game, where players are assumed to be (1) rational, in that they make self-interested decisions that maximize some expected game payoff measured by some utility, and (2) intelligent, in that they know everything about the game the modeler knows and can make any inferences about the game the modeler can make (Myerson 1991). There are numerous game distinctions, but the most common are noncooperative and cooperative. Intuitively, noncooperative games involve players who compete and make independent decisions whereas cooperative games involve players who make collective decisions, negotiate, and allocate the benefits of doing so (Madani 2010). Cooperative games with three or more players must employ a theory of coalitional analysis in order to account for the formation of possible multiplayer coalitions (Myerson 1991).

In CGT, game analysis takes into consideration that cooperative subsets, or coalitions, may form within the group of players in their entirety, referred to as the grand coalition (Myerson 1991). CGT allows game theorists to model the capabilities of groups of individuals rather than the individuals themselves (Shoham and Leyton-Brown 2008). A central solution concept in CGT, the Shapley value (Shapley 1953), associates a unique game payoff value with each coalition member (Hart 2008). In other words, a player's Shapley value is the player's average marginal contribution (AMC) to a game payout, weighted and summed over all possible player combinations (Molnar 2022; Shoham and Leyton-Brown 2008). In this sense, it is a useful measure of individual players' power in a coalitional game (Myerson 1991). It is also used as a measure of fairness when allocating game payouts, according to symmetry, dummy player, and additivity axioms (Myerson 1991; Shapley 1953; Shoham and Leyton-Brown 2008). The Shapley value of player i, ϕ_i, in game (N, v), can be calculated using the following equation, in which N represents the grand coalition, or set of all players, S is a given coalition, and $v(S)$ is the contribution of coalition S

$$\phi_i(N, v) = \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} |S|!(|N| - |S| - 1)![v(S \cup \{i\}) - v(S)] \tag{1}$$

Characteristic function v assigns a number value $v(S)$, or worth, to every coalition S. This is possible due to the Shapley value's underlying assumption of the existence of transferable utility. This assumption states that game players may freely transfer units of commodity, usually in the form of money, among themselves. With each unit of commodity a player gains, their payoff increases (Myerson 1991). The following section explains how these concepts are applied to stormwater management to inform GI spending and planning decisions.

Game Design and Implementation

This research employed the CGT solution, known as the Shapley value, to inform GI allocation across the five Market Street watershed subbasins by observing total watershed flood damage cost reductions following the 2015 1,000-year flood in different installation scenarios. Four unique games and two variations of one of these games were designed and implemented for the Market Street watershed model executed in PCSWMM.

Subbasin buildings, categorized according to available zoning data, were assigned either Residential (Household) or Commercial (Business) identifiers. GI types considered in the presented games were limited to rooftop-connected rain barrels and cisterns due to their relative physical and economic accessibility to the individual. In all games it was assumed that a maximum of one rain barrel and one cistern could be installed per Residential and Commercial building, respectively. As PCSWMM does not allow users to assign LIDs to specific buildings, the impervious area treated in each subbasin was calculated using the average size of each building type per subbasin. Rainwater harvesting costs and design specifications are provided in Table 1 (Wayfair 2022; Tank Depot 2022a, b).

Unique games were proposed to observe the effects of varying hypothetical spending amounts, GI grants, impervious area treatment minimums, and minimum rainwater storage requirements. Each game was simulated with the following conditions: (1) barrels and cisterns had no underdrains, so LIDs only filled one time over the course of the simulation, and (2) barrels and cisterns had a 12-h drain delay, which occurred after rainfall had ceased for 12 h.

For the storm event used in this study, barrels and cisterns, when applicable, drained twice over the course of the simulation; once at Hour 40, and again at Hour 110. Drains were each assigned a 2-in.-diameter and a 6-in. offset height, and drain coefficients were calculated according to procedures outlined in the SWMM manual (EPA and Rossman 2015). Each game was implemented in PCSWMM using the software's LID Usage Editor to place LIDs according to the game descriptions. An n player coalitional game would produce $(2^n - 1)$ possible player combinations; therefore, each game required 31 model runs in PCSWMM, each simulating different subbasin combinations of LID installation. PCSWMM results included total flood volume for each scenario, used to

Table 1. Rain barrel and cistern design specifications and costs

Variable	Rain barrel	Rain cistern A	Rain cistern B
Building type	Residential	Commercial	Commercial
Size (L)	227.4 (60-gal.)	7,580 (2,000-gal.)	18,950 (5,000-gal.)
Cost (USD)	115	1,680	4,300
Unit area (m^2)	0.29	4.1	5.3
Unit height (m)	0.9	2.4	3.9

calculate total flood damage costs for each subbasin and the Market Street watershed system. This process is discussed in the following subsection.

In terms of the Shapley solution, the contribution value of each subbasin coalition, $v(S)$, was represented by each subbasin's capacity to reduce flood damage cost for the entire Market Street watershed. Coalition S could consist of any combination of players, represented by the five Market Street subbasins. These subbasins were assigned Identifiers A through E (Fig. 2). If a subbasin was in a coalition, it was assumed to have participated in LID implementation. For example, Coalition A described a scenario in which Subbasin A installed LIDs according to game rules and Subbasins B, C, D, and E did not. Hence, the Shapley value of Subbasin A, ϕ_A, represented Subbasin A's AMC to the total system flood damage cost reduction after considering its contribution to the system in every possible coalition combination. The grand coalition henceforth refers to Coalition ABCDE, the player combination in which all subbasins participated in LID installation; alternately, the empty set describes the baseline scenario in which none of the players took part in LID installation.

The Shapley value served as a metric of power for each subbasin, illustrating which subbasins contributed most to overall system flood damage reduction, informing future planning decisions, in terms of where GI advocacy efforts should be focused, incentives offered, or LID projects installed. Additionally, in running every combination of subbasin participation in GI installation, it was possible to compare cost-effectiveness for each subbasin by observing GI cost per basin and individual subbasin flood damage cost reductions.

Flood Damage Cost Calculations

Shapley values were calculated using building flood damage cost reductions as a metric to inform LID placement decisions. These costs were estimated using PCSWMM total flood volume outputs and FEMA HAZUS flood model depth-damage curves (FEMA 2021) to estimate Residential and Commercial building total repair costs (TRC) per subbasin and then summing them for the Market Street watershed. It should be noted that the HAZUS metrics employed in this study to estimate flood damage costs are based primarily on flood depth and building type, although it is known that flood duration can significantly impact flood damage severity and consequent damage repair costs (Wagenaar 2012). To establish the baseline TRC, total flood volume for all junctions in each subbasin was summed. Additional "safe to fail" systems such as parks, golf courses, and other open spaces capable of lessening runoff volumes and velocities were not explicitly considered as none of the subbasins contained developed, open-space land cover that typically includes these systems (Homer et al. 2015). To approximate subbasin flood depths, the following equation was used:

$$\text{Flood Depth}_i = \frac{\text{Total Flood Volume}_i}{\text{Area}_{\text{Basin}(i)} - \text{Area}_{\text{Buildings}(i)}} \quad (2)$$

Once subbasin flood depths were established, all buildings within each subbasin were assumed to experience a uniform level of flooding. Residential TRCs per subbasin were calculated by multiplying the total Residential building area per subbasin by the corresponding HAZUS depth-damage curve (DDC) percentage damage value for Single Family Household, Luxury, No Basement homes, and the HAZUS-designated repair cost (\$2,014.42/flooded m^2). Commercial building TRCs were calculated following the same procedure, using HAZUS DDC values and repair costs for Entertainment and Recreation buildings (\$2,106.35/flooded m^2). These damages were then summed for each subbasin and ultimately the entire Market Street basin to find the TRC for the system. This procedure is summarized in the following equation:

$$\begin{aligned}\text{Market Street Basin TRC} = \sum \Bigg(& \text{Building Area}_{Com(i)} \\ & \times \frac{\text{DDC Value}}{100} \times \text{Repair Cost}_{Com} \\ & + \text{Building Area}_{Res(i)} \times \frac{\text{DDC Value}}{100} \\ & \times \text{Repair Cost}_{Res} \Bigg) \end{aligned} \quad (3)$$

This process was repeated for every coalition combination for every game scenario. To calculate subbasin TRC reduction for each of these instances, each TRC for every coalition combination for every game was subtracted from the baseline TRC. These values were used to calculate subbasin Shapley values for each game, with the following specifications:

1. Maxed—every Residential building had one 227.4-L (60-gal.) rain barrel, and every Commercial building had one 7,580-L (2,000-gal.) cistern. Subbasin total costs and quantities varied. This served as the maximum rainwater-harvesting scenario within user-set barrel size and building type restrictions.
2. Equal storage—each subbasin had 14 identical 7,580-L (2,000-gal.) cisterns and each subbasin had a total cistern cost of \$23,520. A quantity of 14 was selected because it was the number of Commercial buildings in the subbasin with the fewest Commercial buildings. This served as an identical spending and rainwater storage scenario across all subbasins.
3. 20% impervious area treated (IAT)—each subbasin treated a minimum of and as close to 20% of its impervious area as possible using only 7,580-L (2,000-gal.) cisterns. Subbasin total costs and quantities varied. This served as a feasibility test for GI rebate programs that only consider treated area requirements.
4. Maxed—18,950-L (5,000-gal.) cisterns in Subbasin E: Maxed (Game 1) scenario funding for Subbasin A (cisterns only) was transferred to Subbasin E and was added to Subbasin E's existing Maxed scenario funding. With this additional funding, Subbasin E replaced its 16 7,580-L (2,000-gal.) cisterns with 16 18,950-L (5,000-gal.) cisterns. This served as a suggested scenario.
5. Maxed—Rebate A: same as Maxed (Game 1) scenario, but subbasins were reimbursed \$5,000 for every 10% of impervious area treated.
6. Maxed—Rebate B: Same as Maxed (Game 1) scenario, but subbasins were reimbursed \$7,000 for every 15% of impervious area treated.

Results

Model Validation

The one-dimensional Charleston Peninsula model configured in PCSWMM (Lawyer 2022), used to develop the PCSWMM Market Street watershed model, was validated by comparing flow rate results for a segment of the peninsula's drainage network with those achieved in a fully coupled compound flood interconnected channel and pond routing (ICPR) model for the Charleston peninsula under identical rainfall and tide conditions (Tanim et al. 2022). The ICPR model was calibrated and validated based on historical data and flood information for the Charleston peninsula, and thus was used as a benchmark to validate the PCSWMM model presented in this study. Validation methods are further discussed in Appendix S1 of the Supplemental Materials.

Subbasin Characteristics

Characteristics of each of the Market Street subbasins related to area and building density are summarized in Table 2. Building counts and areas per subbasin are listed in Table 3. A map of Residential and Commercial buildings is provided in Fig. 2. Land cover distributions (Multi-Resolution Land Characteristics Consortium 2011), impervious area covered by buildings and edge of pavement (EOP) (City of Charleston Information and Technology GIS Division 2021a, b, c), and existing building and EOP layout were used to create games for analysis that met the physical restraints of each subbasin, as well as to calculate potential treated area in PCSWMM for each subbasin under different LID conditions. All subbasin properties provided in this section lent physical context to and are discussed alongside Shapley value results.

Baseline Total Repair Cost

Total repair cost (TRC) for the baseline scenario was estimated using the described flood damage cost calculation methods and rounding up to the nearest dollar (the uncertainties in the presented methods did not allow results to be accurate to the nearest dollar, but they avoided any situations in which rounding by a larger quantity may have led to misranking of coalition TRC savings). The baseline TRC was estimated to be $10,357,415. Results for the baseline scenario run in PCSWMM indicate that flood volume was not distributed evenly across the subbasins, as Subbasin C accounted for 35% of the total volume, followed by 30% in Subbasin E and 17%, 9%, and 8% in Subbasins D, A, and B, respectively. Thus, Subbasin C bore the highest flood damage cost, accounting for 26% of the TRC, followed by Subbasins B and E accounting for 20% each, Subbasin A for 19%, and Subbasin D for 15%. Differences in shares of flood volume versus flood damage cost were the result of different land use types as well as variation in the number and type of buildings in each subbasin. Ninety-three percent of the watershed TRC was attributed to Commercial building costs, mostly attributed to Subbasins C and E, as these subbasins had the highest flood volumes. Neither subbasin contained Residential buildings, and the HAZUS Commercial repair cost per square foot used in this study exceeded that of Residential buildings. TRC reductions were calculated for all game coalition combinations by subtracting each coalition's TRC from the baseline TRC and were used to measure subbasin Shapley values.

Table 2. Area and building distributions for Market Street watershed subbasins

Subbasin	Watershed total area distribution (%)	Watershed total building distribution (%)	Watershed total building area distribution (%)
A	23	42	24
B	20	17	24
C	18	11	19
D	22	18	17
E	16	13	16

Table 3. Number and total area per building type per Market Street subbasin

Subbasin	Total residential buildings	Total residential building area (m^2)	Total commercial buildings	Total commercial building area (m^2)
A	27	5,920	25	27,958
B	4	1,420	17	33,219
C	0	0	14	27,078
D	8	2,819	14	20,882
E	0	0	16	22,689

Game Analysis: Shapley Value and Cost Comparisons

Shapley values for each game are presented in this section. In Game 1, Maxed, all Households installed one 227.4-L (60-gal.) barrel, and all Businesses installed one 7,580-L (2,000-gal.) cistern. Subbasins had varying storage capacities and LID costs. Number and percentage of participating players, total GI cost, and IAT as input in PCSWMM's LID Usage Editor for each game are provided in Table 4. Shapley value results and total spending were presented for the no underdrain and 12-h drain delay Maxed scenarios are

Table 4. LID quantities, cost, and IAT for all games

	Households with LIDs		Businesses with LIDs			
Subbasin	Number	Percentage of total	Number	Percentage of total	% IAT	GI cost
Game 1—Maxed						
A	27	100	25	100	48.5	$45,105
B	4	100	17	100	57.0	$29,020
C	—	—	14	100	47.2	$23,520
D	8	100	14	100	36.6	$24,440
E	—	—	16	100	43.2	$26,880
Game 2—Equal storage						
A	0	0	14	56	22.4	$23,520
B	0	0	14	82.4	45.1	$23,520
C	—	—	14	100	47.2	$23,520
D	0	0	14	100	31.8	$23,520
E	—	—	14	87.5	37.8	$23,520
Game 3—20 IAT						
A	0	0	13	52	20.8	$21,840
B	0	0	7	41.2	22.5	$11,760
C	—	—	6	42.9	20.3	$10,080
D	0	0	9	64.3	20.4	$15,120
E	—	—	8	50	21.6	$13,440
Game 4—Maxed, 18,950-L cisterns in Subbasin E						
A	24	100	0	0	8.5	$3,105
B	4	100	17	100	57.0	$29,020
C	—	—	14	100	47.2	$23,520
D	8	100	14	100	36.6	$24,440
E	—	—	16	100	43.2	$68,880
Game 5—Maxed, Rebate A						
A	27	100	25	100	48.5	$25,105
B	4	100	17	100	57.0	$4,020
C	—	—	14	100	47.2	$3,520
D	8	100	14	100	36.6	$9,440
E	—	—	16	100	43.2	$6,880
Game 6—Maxed, Rebate B						
A	27	100	25	100	48.5	$22,472
B	4	100	17	100	57.0	$2,420
C	—	—	14	100	47.2	$1,493
D	8	100	14	100	36.6	$7,360
E	—	—	16	100	43.2	$6,720

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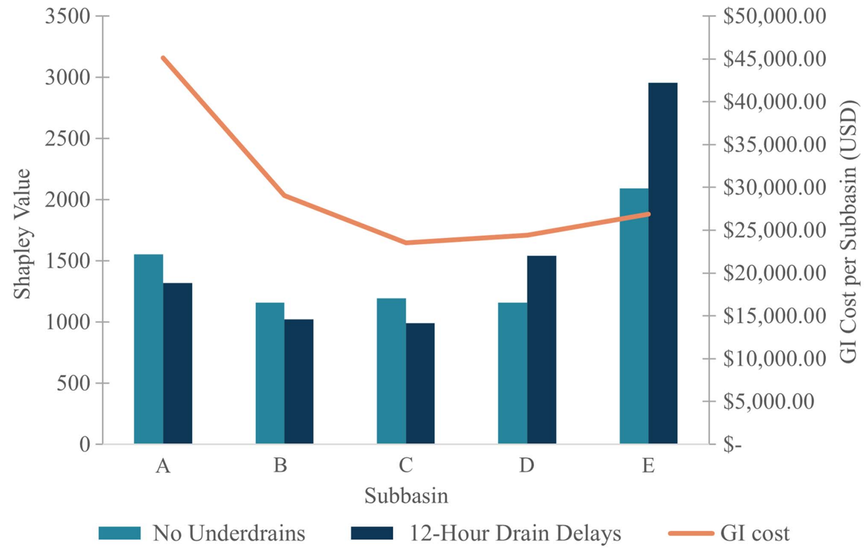

Fig. 3. Game 1—Maxed: subbasin Shapley values and total GI cost.

shown in Fig. 3. Cost-effectiveness, shown as TRC savings per GI dollar spent and henceforth referred to as the spent-saved ratio (SSR), are shown for the No Underdrains and 12-h Drain Delay scenarios for all games in Appendix S7, Tables S1 and S2, respectively, in the Supplemental Materials. While TRC savings were taken into consideration for each coalition per game through calculation of their respective SSR values, explicit TRC savings for each coalition and game scenario are listed in Appendix S2 of the Supplemental Materials, and select quantities are referred to here when beneficial to the discussion and comparison of results. In the No Underdrains scenario, Subbasin E had the highest Shapley value, and therefore the highest AMC of all subbasins to watershed TRC savings, while also having the third lowest GI cost. Subbasin A had the second highest Shapley value but a significantly higher cost, nearly double that of Subbasin E, as it had the highest number of both building types and consequently the highest number of purchased barrels and cisterns. The AMC of Subbasin E was nearly double that of Subbasins B, C, and D, only with additional spending of nearly $2,000. In this case, the grand coalition provided the watershed with the highest overall flood damage savings, but was not the most cost-effective coalition, as it did not have the lowest SSR. The lowest SSR belonged to the coalition containing only Subbasin E, followed by Coalitions DE, CE, C, BE, D, CDE, and so forth, illustrating that the most cost-effective GI planning options were those that included spending in Subbasin E and excluded spending in Subbasin A, which had the highest SSR, meaning that Subbasin A was the least cost-effective place to focus GI spending for flood damage reduction. The grand coalition generated the highest overall flood damage savings of $9,569. These findings were significant as they indicated that watershed GI spending would go farther in the way of flood reduction in Subbasin E than in any other subbasin.

With 12-h drain delays, Subbasin E still offered the highest Shapley value, and exceeded the Shapley value obtained in the no underdrain scenario. Subbasin D, which shared the lowest Shapley value with Subbasin B in the previous scenario, had the second highest Shapley value, exceeding Subbasin A at approximately half the GI cost. Subbasin E still had the lowest SSR, followed by Coalitions DE, CE, D, BE, BDE, and CDE. However, in this case the grand coalition had the highest TRC reduction and SSR, acting as the least cost-effective option for flood damage savings. The grand coalition saved the watershed $12,603, which was greater than its achieved savings in the no underdrain scenario but less than Coalition ADE in the 12-h Drain Delay scenario, which had the potential to save the watershed a total of $14,782.

The differences in Shapley value distributions for the two underdrain scenarios made it apparent that upstream LID drain release times in each subbasin influenced downstream subbasin flood damage reduction abilities. Hydrographs illustrating these are provided in Appendices C through F in the Supplemental Materials.

In Game 2, Equal Storage, all subbasins installed 14 cisterns and therefore had equivalent GI costs and rainfall storage capacities while treating different amounts of impervious area, as these values were dependent on subbasin average Commercial building sizes. Shapley value results and total spending are presented for the two drain scenarios in Fig. 4. With no underdrains, Subbasin E had the highest Shapley value. The coalition that saved the system the most in TRC was the one that consisted of only Subbasin E, and also had the lowest SSR, making it the most cost-effective GI plan. Again, it was found that coalitions that contained Subbasin E were the most cost effective, with Coalitions DE, CE, BE, D, C, and CDE following with the next lowest SSR values. Subbasin A was still the least cost-efficient option. The grand coalition saved the system $8,656 in TRC.

When cisterns had a 12-h drain delay, Shapley values increased for all subbasins, but maintained the same relation to one another as in the no underdrain scenario, increasing from Subbasin A to Subbasin E. Subbasin A was still contributing the least to overall TRC reduction, only treating 22.4% of its impervious area in this game versus 100% in the previous game, and it was still the least cost-efficient option. The grand coalition saved the system $13,205 in TRC, but the highest TRC savings for this game scenario were brought about by Coalition ACDE, saving $14,278, implying that the addition of and spending on GI with 12-h drain delays in Subbasin B created additional flood damage. Here, it was again shown that drain delays on widely distributed GI can affect hydrological processes and outcomes within the watershed.

In Game 3, 20% IAT, each subbasin treated a minimum of and as close to 20% of its impervious area using 7,580-L (2,000-gal.) cisterns. Shapley value results and total spending are presented for the two drain scenarios in Fig. 5. With no underdrains, Subbasin E again had the highest Shapley value, having the highest AMC to

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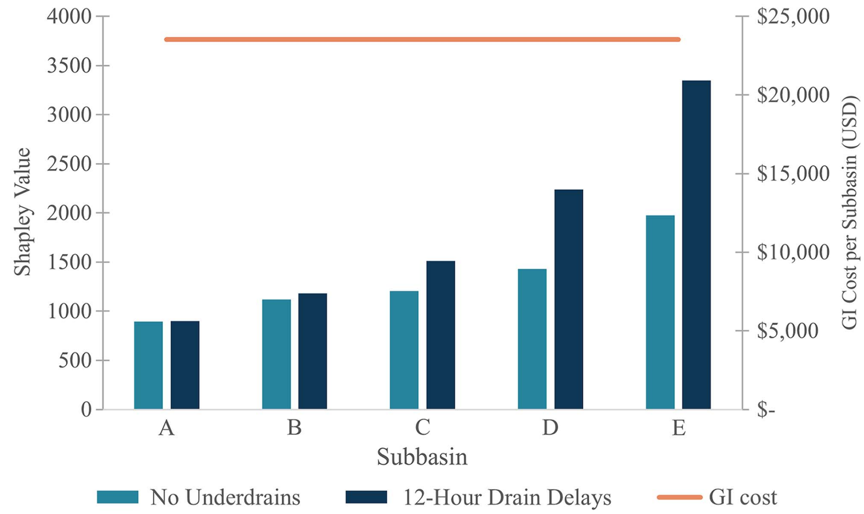

Fig. 4. Game 2—Equal storage: subbasin Shapley values and total GI cost.

TRC savings for the entire watershed and treating approximately 20% of its area at a lower cost than both Subbasins A and D. As in the previous games, Subbasin E had the lowest SSR and was the most cost-effective option for GI installation, and Subbasin A had the highest SSR. The grand coalition in this case saved the watershed $5,590 and was the coalition with the highest TRC savings.

When 12-h cistern drain delays were employed, Shapley values increased for all subbasins, and Subbasin E's value more than doubled. The subbasins remained in the same order of increasing AMCs as in the no underdrain scenario, aside from Subbasin C having the lowest Shapley value rather than Subbasin B. As in the previous scenario, Subbasins E and A were the most and least cost-effective locations for GI focus, respectively. The grand coalition in this instance saved the watershed $11,571 in TRCs. This was the first game in which the No Underdrain and Drain Delay scenario grand coalitions both resulted in the highest TRC savings. This may have been due to considerably higher IAT values across the subbasins in the first two games, so the stormwater volume released after the two drain delays did not have a significant effect on neighboring subbasins by way of increased flood depth.

In Game 4, Maxed, 18,950-L (5,000-gal.) Cisterns in Subbasin E, the setup mirrored Game 1, but a portion of Subbasin A's GI funding was given to Subbasin E to address the fact that Subbasin E was the most cost-effective location for GI placement in all other games. Subbasin A kept its Residential barrels, but no longer had funding for its 25 Commercial cisterns. The cost of these 25 7,580-L (2,000-gal.) cisterns was given to Subbasin E and used to install 18,950-L (5,000-gal.) cisterns on all 16 of its Commercial buildings rather than the 16 7,580-L (2,000-gal.) cisterns it had previously. Shapley value results and total spending are presented for the two drain scenarios in Fig. 6. As expected, in the No Underdrains scenario, Subbasin A installed barrels only for its Residential properties and had the lowest GI cost and Shapley value, and Subbasin E spent more than double what Subbasins B, C, and D spent, and had a Shapley value approximately five times higher. Similar to previous games, Subbasins E and A had the lowest and highest SSR values, respectively. The grand coalition provided the watershed's highest TRC savings, a total of $13,270.

In the 12-h Drain Delay scenario, Subbasins A and E still had the lowest and highest Shapley values, respectively, as well as the highest and lowest SSRs, respectively. Shapley values did not

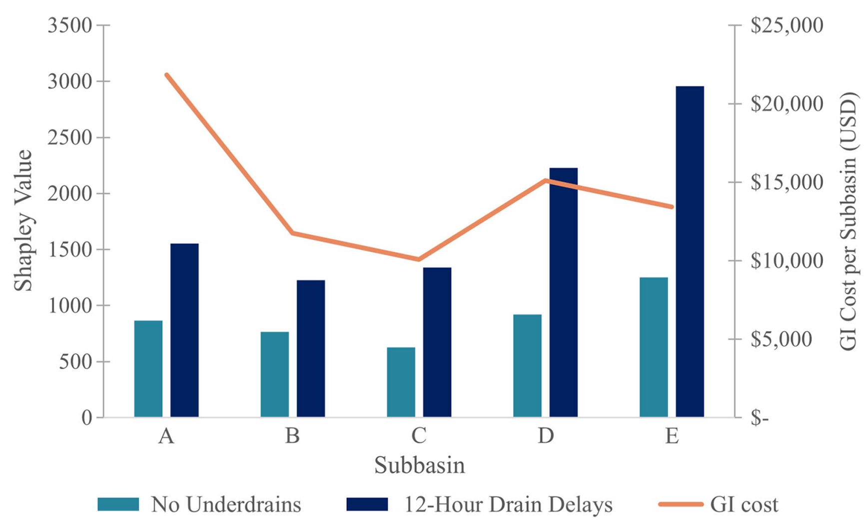

Fig. 5. Game 3—20% IAT: subbasin Shapley values and total GI cost.

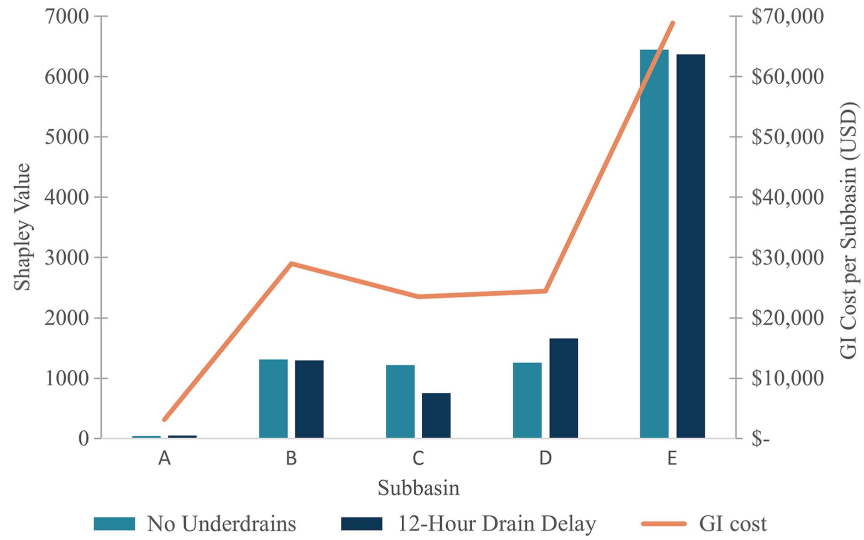

Fig. 6. Game 4—Maxed, 18,950-L (5,000-gal.) cisterns in Subbasin E: subbasin Shapley values and total GI cost.

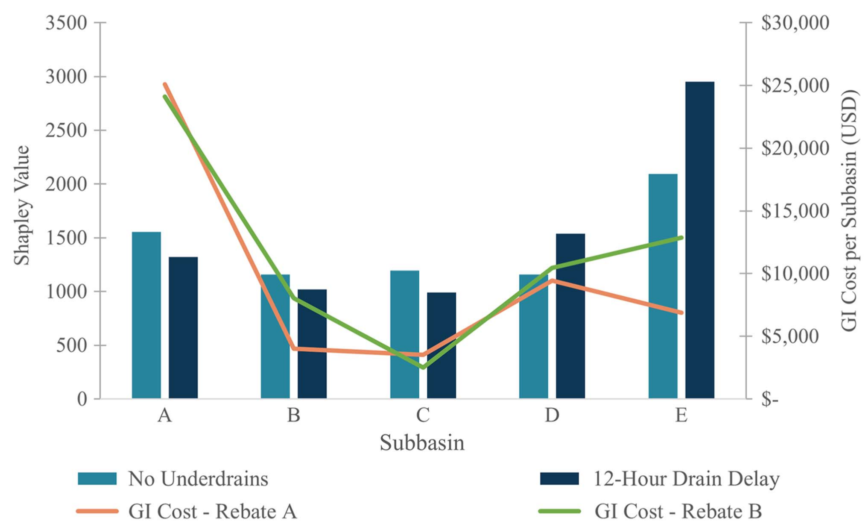

Fig. 7. Games 5 and 6—Maxed, Rebate A versus Rebate B: subbasin Shapley values and total GI costs.

strictly increase with GI spending in this case, as AMCs to TRC savings decreased for Subbasins B, C, D, and E. The grand coalition provided a TRC reduction of $15,296, but flood damage cost reductions were higher under Coalition ABDE, which produced $17,177 in savings, the highest of all games considered thus far.

Finally, to observe the effects of GI rebates on cost-effectiveness across the watershed, two variations of the Game 1: Maxed scenario were considered. The rebate amounts in these games, while selected arbitrarily, served to explore how GI reimbursement programs could potentially affect coalition bargaining power. In the first, Game 5: Maxed, Rebate A, each subbasin was reimbursed $5,000 in GI cost for every 10% of its IAT through rainwater harvesting. Shapley values were unchanged, but they are shown for both drainage scenarios against new rebate-affected GI costs in Fig. 7. Coalition flood damage savings were unchanged from Game 1.

In Game 6, Maxed, Rebate B, each subbasin's GI cost was reimbursed $7,000 per 15% of its impervious area treated through rainwater harvesting. Shapley values and new costs for both drainage scenarios against new rebate-affected GI costs are shown in Fig. 7 and coalition TRCs were still unchanged from Game 1. Total rebate savings for Games 5 and 6 are shown in Table 5. Subbasins B, D, and E saved more on GI spending under the application of Rebate A while Subbasins A and C saved more under Rebate B. In both cases and for all drain scenarios, Subbasin A was the least cost-effective option, saving the lowest amount of flood reduction dollars per GI dollar spent. Most notably, in Games 5 and 6, for the first time, Subbasin E did not had the lowest SSR.

Table 5. GI cost Rebate savings per subbasin

Subbasin	Game 5: Rebate A	Game 6: Rebate B
A	$20,000	$21,000
B	$25,000	$21,000
C	$20,000	$21,000
D	$15,000	$14,000
E	$20,000	$14,000

In all drain scenarios where rebates were enacted, Subbasin C had the lowest SSR. In both scenarios with no underdrains, the most cost-effective coalition, C, was followed by Coalitions CE, BC, and E. Under Rebate A, the 12-h Drain Delay scenario's lowest SSR coalition was C, followed directly by Coalition E. Under Rebate B, the 12-h drain release again had an effect on subbasin storage capacity, as Subbasin E had the fifth lowest SSR in this case—the highest value it had had in any game.

Discussion

Shapley values and cost comparisons for varying GI implementation plans under historic South Carolina 2015 flood event conditions, using the urban flood modeling tool PCSWMM, were estimated and used to identify which subarea, or subareas, of the Market Street watershed should be the focus of governing bodies and planners aiming to either implement GI or focus GI advocacy for the purpose of reducing property damage due to compound flooding. It should be noted that the presented findings were specific to the high-risk, low-probability storm event selected as the case study for this research. The monetary savings, and in turn the Shapley values, obtained for each game, will vary in simulations of smaller, more frequent storm events, as will GI placement and advocacy focus recommendations presented as the results of this study.

Findings for all games are summarized in Table 6. Across all tested GI plans, Subbasin E had the highest AMC to flood-induced cost savings for the Market Street watershed overall, even though Subbasin C experienced the highest flood damage costs in the baseline scenario. Overwhelmingly, Coalition E also had the lowest SSR, saving more in TRC per GI dollars spent than any other coalition in every case aside from Games 5 and 6, in which rebates were considered in the cost efficiency metric. This was likely due to several factors inherent to Subbasin E, including that it had the smallest subbasin area, causing flood depth measurements over the subbasin to be higher than some neighboring subbasins that received a uniform amount of rainfall. Additionally, Subbasin E had the lowest infiltration capacity and the highest percentage of high-intensity developed land cover. Most significant depression areas in the watershed were also in this subbasin, lining Market Street itself. Finally, Subbasin E was connected to Outfall 6.5 (Fig. 2), one of two outfalls in the watershed that were tidally influenced and that had the highest inflow volume across all simulated games, therefore making the drainage network in Subbasin E particularly vulnerable to backflow-induced flooding.

The use of CGT in conjunction with PCSWMM allowed consideration of other factors in addition to determination of the subbasin that experienced the most baseline flooding, which, considered alone, would have suggested that GI be focused in Subbasin C. Shapley values, based on total flood damage costs, encompassed PCSWMM inputs and flooding results, which inherently consider other factors that pointed to Subbasin E being the ideal location for GI focus, such as a relatively small pervious area, a high ratio of developed land cover, and a small subbasin area. The games that instituted rebates were the only scenarios where Subbasin C was considered the most cost-efficient location for GI under Maxed conditions.

In both games that instituted rebates, Subbasin C received the same amount or more in rebates for GI than Subbasin E. Subbasin C saved an additional $7,000 under Rebate B conditions, even though it was treating only an additional 4% of its IAT. However, under Equal Storage and spending conditions in Game 2, Subbasin E had higher Shapley values than Subbasin C in both drainage scenarios, and therefore higher AMCs to overall watershed TRC savings. In every other game scenario explored, Subbasin E alone was the most cost-effective option for GI placement, suggesting this would be the recommended area for GI focus. From a policy standpoint, these results suggest that governing bodies offering GI spending assistance or rebates based solely on community or watershed IAT benchmarks fail to take into consideration total area, building GI capacity, flood reduction need, and the like.

Coalition A provided the lowest cost reduction returns per GI dollar spent, and Subbasin A had the lowest Shapley value for both drainage scenarios in the Equal Storage and, expectedly, in the Maxed, 18,950-L (5,000-gal.) Cisterns in Subbasin E games. In the other Maxed scenarios, Subbasin A consistently had the highest GI cost because it contained the highest number of buildings. Even in the 20% IAT scenario, Subbasin A had to spend double what Subbasins B and C spent on GI to reach the 20% IAT benchmark due to its relatively small average building size. These high-cost, low-return results led to the suggested scenario where Subbasin E received Subbasin A's Maxed cistern funding to install larger cisterns, and this scenario saved the watershed the most flood damage

Table 6. Summary of game results: Shapley values, SSRs, and coalition TRC savings

		Highest Shapley value		Lowest Shapley value		Highest TRC savings			Lowest SSR		
Game	Drain scenario	Subbasin	Value	Subbasin	Value	Coalition	Savings	SSR	Coalition	Savings	SSR
1	No underdrain	E	2,092	B and D	1,158	ABCDE	$9,569	15.6	E	$3,376	8.0
	12-h delay	E	2,953	C	991	ADE	$14,782	6.5	E	$7,509	3.6
2	No underdrain	E	1,975	A	893	ABCDE	$8,656	13.6	E	$2,946	8.0
	12-h delay	E	3,347	A	898	ACDE	$14,278	6.6	E	$6,630	3.5
3	No underdrain	E	1,253	C	627	ABCDE	$5,590	12.9	E	$1,726	7.8
	12-h delay	E	2,956	B	1,226	ABCDE	$11,571	6.2	E	$3,781	3.6
4	No underdrain	E	6,446	A	39	ABCDE	$13,270	11.2	E	$8,558	8.0
	12-h delay	E	6,369	A	50	ABDE	$17,177	7.3	E	$13,558	5.1
5	No underdrain	E	2,092	B and D	1,158	ABCDE	$9,569	5.1	C	$3,376	1.6
	12-h delay	E	2,953	C	991	ADE	$14,782	2.8	C	$7,509	0.9
6	No underdrain	E	2,092	B and D	1,158	ABCDE	$9,569	6.1	C	$3,376	1.2
	12-h delay	E	2,953	C	991	ADE	$14,782	3.2	C	$7,509	0.6

repair costs in both drainage scenarios out of all modeled games, the highest being the 12-h Drain Delay scenario with a TRC of approximately $17,200 for the watershed.

Finally, the drain scenario comparisons were valuable in their ability to show that while rainwater harvesting for water recycling and cost savings in a home or business could be beneficial, the Drain Delay scenarios unsurprisingly allowed for more flood damage savings for the watershed as a whole. Additional analysis could be performed to determine more advantageous drain times and barrel locations, as the hydrographs provided in the Supplemental Materials give insight into how simultaneous draining of even Residential-size barrels, when distributed widely enough, can influence downstream stormwater management capacity. Most notable is the Shapley value analysis, which unintuitively showed that the watershed saved more in TRC under coalitions other than the grand coalition when LIDs had 12-h drain delays instituted in multiple games, including Coalitions ADE in Game 1, ACDE in Game 2, and ABDE in Game 4.

Conclusion and Closing Remarks

Game theory can be used to predict outcomes of human decision-making when self-interested parties are faced with conflict. Cooperative, and in this case, coalitional analysis, is used to predict how self-interested parties may form to better their individual outcomes. For this research, a CGT solution, the Shapley value, was leveraged to observe how subgroups should work together to better serve the overall system and by association themselves. The results of this research will serve to inform governing bodies, city planners, and relevant stakeholders that subareas benefit the system most, through flood damage repair cost savings and cost efficiency. Even without the intention of government-level GI project installation, these results indicated where GI information campaigns should be focused to encourage individual property owners to participate in stormwater management strategies. Additionally, CGT shows which areas of the watershed working in conjunction are the best for the watershed overall, so planners can strategically work in more than one community, neighborhood, or modeled subarea at a time. Overall, based on Shapley values and the cost efficiency metric used here, the results suggest GI spending, placement, and advocacy focus in Subbasin E, surrounding Market Street itself.

Of course, results would vary widely under a different set of modeling constraints and assumptions—for example if buildings had more than one means of rainwater harvesting, if homeowners association restraints were considered for residential properties, or if commercial buildings were additionally outfitted with underground cisterns. Regardless of the assumptions in place, the application of CGT to stormwater modeling and flood reduction allows consideration of budget constraints, basin area, land cover and drainage characteristics, rainfall-runoff processes, and both building and property size, type, and location simultaneously.

Additionally, the methods described here are highly versatile, as what the Shapley value measures is up to the discretion of the modeler and PCSWMM can model any number of environmental conditions and storm events. If the Shapley values measured not cost reductions but overall flood volume reduction, there would be an entirely different analysis to be had. Leveraging PCSWMM results, Shapley values could be based on subcatchments' flood volume reduction, junction inflows, subbasin peak runoff values, or any number of other parameters, to compare any number of land development changes or GI choices. Further, this study solely explored GI to address the rainfall component of compound flooding, and future analysis would benefit from the introduction of commonly used protection measures for tidal flooding.

The authors acknowledge the limitations of this study, as property damage results and consequent costs and Shapley values, are highly sensitive to the flood depths achieved in the presented stormwater model, whose accuracy and insight could only be improved through 2D modeling capabilities, ponding, and flood duration considerations. The modeled scenarios, depicting simultaneous and widespread installation of GI by independent parties, are undeniably disconnected from more realistic and often piecemeal industry practices. Additionally, the human behavior modeled in this study is achieved through the assumption that agents will choose to take actions that increase their own payoffs, revealing which coalitions have the highest payoffs and therefore are the most likely to form. The assumption in this study, that all subbasins and by association the individuals in them seek a shared payoff of reducing system flood damage repair costs, was admittedly idealistic. Further, individuals across any modeled system will possess a variety of backgrounds with varying economic status and beliefs, among other things, about personal responsibility in the realm of stormwater management, none of which the game theory analysis presented here considered. The levels of voluntary GI simulated in this study will be much harder to achieve in practice due to these heterogeneities and a variety of barriers and beliefs among the individuals making up the coalitions modeled here. The results of the coalitional analysis are more useful for informing future behavior by planners and decision makers hoping to spend GI advocacy and installation funds wisely than for approximating the behavior of individuals. Overall, there are potential advantages of a more holistic approach to flood management, but they require deeper understanding of the nuanced interactions needed to encourage and institute such a high level of community cooperation. Additional suggestions for future work include the following:

- Use of a two-dimensional hydrodynamic model to simulate compound flooding and dynamic boundary conditions for the Charleston Peninsula.
- Development of a less computationally complex and time-intensive simulation model capable of managing more players and coalitions.
- Consideration of stakeholder and water manager input when developing game scenarios and incorporating different storm intensities and frequencies with respect to real-world civil engineering designs.
- Exploration of remaining questions about uncertainty analysis and the scalability of infrastructure implementation.
- Simulation of additional design storms, future storms, and flood events under projected climate conditions to develop stochastic games and estimate Shapley values.
- Application of the presented methods to other varieties and combinations of green and traditional flood infrastructure.
- Introduction of uncertainty in player behavior by combining game theory applications with hierarchical ABM strategies.
- Development of additional human behavior studies concerning individual likelihood of taking part in green stormwater management strategies and common barriers, as described for residents of South Carolina's coastal counties in Ureta et al. (2021).
- Open dialogue with historic property owners and city managers to determine appropriate adaptation strategies for their sites in order to design feasible modeling institutions and flood adaption options for specific properties.

As sea levels climb at accelerated rates and climate variations continue to alter storm intensity and frequency, the world's coastal communities will become increasingly vulnerable to the unequally distributed risks associated with the coupling of these events.

Stakeholders and the public will need novel approaches and nuanced responses to the combined effects of tide- and stormwater-induced flooding. Planners will be faced with increasingly difficult decisions regarding prioritization of infrastructure and related spending that can only stand to be improved by further exploration of human choices and consequent outcomes in water resources management.

Data Availability Statement

The authors confirm that the derived data supporting the findings of this study are available in the article and the Supplemental Materials. Other required data, such as model and model parameters, are available from the corresponding author upon reasonable request.

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Supplemental Materials

Appendixes S1–S7, Figs. S1–S57, and Tables S1 and S2 are available online in the ASCE Library (www.ascelibrary.org).

References

Abebe, Y. A., A. Ghorbani, I. Nikolic, N. Manojlovic, A. Gruhn, and Z. Vojinovic. 2020. "The role of household adaptation measures to reduce vulnerability to flooding: A coupled agent-based and flood modelling approach." *Hydrol. Earth Syst. Sci. Discuss.* 2020 (Jul): 1–40. https://doi.org/10.5194/hess-2020-272.

Abebe, Y. A., A. Ghorbani, I. Nikolic, Z. Vojinovic, and A. Sanchez. 2019a. "A coupled flood-agent-institution modelling (CLAIM) framework for urban flood risk management." *Environ. Modell. Software* 111 (Jan): 483–492. https://doi.org/10.1016/j.envsoft.2018.10.015.

Abebe, Y. A., A. Ghorbani, I. Nikolic, Z. Vojinovic, and A. Sanchez. 2019b. "Flood risk management in Sint Maarten–A coupled agent-based and flood modelling method." *J. Environ. Manage.* 248 (Oct): 109317. https://doi.org/10.1016/j.jenvman.2019.109317.

Ahern, J. 2011. "From fail-safe to safe-to-fail: Sustainability and resilience in the new urban world." *Landscape Urban Plann.* 100 (4): 341–343. https://doi.org/10.1016/j.landurbplan.2011.02.021.

Ahiablame, L., and R. Shakya. 2016. "Modeling flood reduction effects of low impact development at a watershed scale." *J. Environ. Manage.* 171 (Apr): 81–91. https://doi.org/10.1016/j.jenvman.2016.01.036.

Ahiablame, L. M., B. A. Engel, and I. Chaubey. 2013. "Effectiveness of low impact development practices in two urbanized watersheds: Retrofitting with rain barrel/cistern and porous pavement." *J. Environ. Manage.* 119 (Apr): 151–161. https://doi.org/10.1016/j.jenvman.2013.01.019.

An, L., M. Linderman, J. Qi, A. Shortridge, and J. Liu. 2005. "Exploring complexity in a human-environment system: An agent-based spatial model for multidisciplinary and multiscale integration." *Ann. Assoc. Am. Geogr.* 95 (1): 54–79. https://doi.org/10.1111/j.1467-8306.2005.00450.x.

Bai, Y., N. Zhao, R. Zhang, and X. Zeng. 2018. "Storm water management of low impact development in urban areas based on SWMM." *Water* 11 (1), https://doi.org/10.3390/w11010033.

Bandini, S., S. Manzoni, and G. Vizzari. 2009. "Agent based modeling and simulation: An informatics perspective." *J. Artif. Soc. Social Simul.* 12 (4): 4.

Baptiste, A. K., C. Foley, and R. Smardon. 2015. "Understanding urban neighborhood differences in willingness to implement green infrastructure measures: A case study of Syracuse, NY." *Landscape Urban Plann.* 136 (Apr): 1–12. https://doi.org/10.1016/j.landurbplan.2014.11.012.

Bates, B. C., S. W. Kundzewicz, and J. P. Palutikof. 2008. "Climate change and water: IPCC technical paper VI." Accessed September 1, 2023. https://www.ipcc.ch/site/assets/uploads/2018/03/climate-change-water-en.pdf.

Berglund, E. Z. 2015. "Using agent-based modeling for water resources planning and management." *J. Water Resour. Plann.* 141 (11): 04015025. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000544.

Bliss, D. J., R. D. Neufeld, and R. J. Ries. 2009. "Storm water runoff mitigation using a Green roof." *Environ. Eng. Sci.* 26 (2): 407–418. https://doi.org/10.1089/ees.2007.0186.

Braden, J., J. Eheart, and R. Saleth. 1991. "Bargaining rules for a thin spot water market." *Land Econ.* 67 (3): 326–339. https://doi.org/10.2307/3146428.

Carter, T., and L. Fowler. 2008. "Establishing green roof infrastructure through environmental policy instruments." *Environ. Manage.* 42 (Jul): 151–164. https://doi.org/10.1007/s00267-008-9095-5.

CEMHS (Center for Emergency Management and Homeland Security). 2020. "The Spatial Hazard Events and Losses Database for the United States, V. 17.0." ASU Center for Emergency Management and Homeland Security. Accessed September 1, 2022. http://www.sheldus.org.

Chaffin, B. C., W. D. Shuster, A. S. Garmestani, B. Furio, S. L. Albro, M. Gardiner, M. Spring, and O. O. Green. 2016. "A tale of two rain gardens: Barriers and bridges to adaptive management of urban stormwater in Cleveland, Ohio." *J. Environ. Manage.* 183 (Dec): 431–441. https://doi.org/10.1016/j.jenvman.2016.06.025.

Charleston County. 2010. "History." Charleston, SC Official Website. Accessed September 1, 2023. https://www.charleston-sc.gov/2010/History.

City of Charleston. 2015. *Sea level rise strategy: Charleston, South Carolina*. Charleston, SC: City of Charleston.

City of Charleston. 2023. "Charleston rainproof." Accessed September 1, 2023. https://www.charleston-sc.gov/rainproof.

City of Charleston Information and Technology GIS Division. 2021a. "Buildings." City of Charleston GIS. Accessed September 1, 2023. https://gis.charleston-sc.gov/.

City of Charleston Information and Technology GIS Division. 2021b. "Edge of pavement." City of Charleston GIS. Accessed September 1, 2023. https://gis.charleston-sc.gov/.

City of Charleston Information and Technology GIS Division. 2021c. "Zoning map." City of Charleston GIS. Accessed September 1, 2023. https://gis.charleston-sc.gov/.

Climate Engine. 2021. "ASCE grass reference evapotranspiration dataset." Accessed September 1, 2023. https://app.climateengine.com/climateEngine.

Coleman, S., S. Hurley, D. Rizzo, C. Koliba, and A. Zia. 2018. "From the household to watershed: A cross-scale analysis of residential intention to adopt green stormwater infrastructure." *Landscape Urban Plann.* 180 (Dec): 195–206. https://doi.org/10.1016/j.landurbplan.2018.09.005.

Davis, A. P. 2008. "Field performance of bioretention: Hydrology impacts." *J. Hydrol. Eng.* 13 (2): 90–95. https://doi.org/10.1061/(ASCE)1084-0699(2008)13:2(90).

Dawson, R. J., R. Peppe, and M. Wang. 2011. "An agent-based model for risk-based flood incident management." *Nat. Hazards* 59 (Oct): 167–189. https://doi.org/10.1007/s11069-011-9745-4.

Eckart, K., Z. McPhee, and T. Bolisetti. 2018. "Multiobjective optimization of low impact development stormwater controls." *J. Hydrol.* 562 (Jul): 564–576. https://doi.org/10.1016/j.jhydrol.2018.04.068.

Ellis, K., S. Whiteside, E. Smith, C. Berg, D. Caraco, S. Drescher, G. Hoffmann, B. Keppler, M. LaRocco, and A. Turner. 2014. "Low impact development in coastal South Carolina: A Planning and design guide." Accessed September 1, 2023. http://www.northinlet.sc.edu/LID.

EPA. 2014. "Climate change indicators in the United States, 2014 3rd Edition." Accessed September 1, 2023. www.epa.gov/climatechange/indicators.

EPA. 2018. "Urban runoff: Low impact development." Accessed September 1, 2023. https://www.epa.gov/nps/urban-runoff-low-impact-development.

EPA and L. A. Rossman. 2015. "Storm water management model user's manual version 5.1." Accessed September 1, 2023. https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100N3J6.TXT.

Farooqui, A. D., and M. A. Niazi. 2016. "Game theory models for communication between agents: A review." *Complex Adapt. Syst. Model.* 4 (13): 1–31. https://doi.org/10.1186/s40294-016-0026-7.

FEMA. 2021. "HAZUS." Accessed September 1, 2023. https://msc.fema.gov/portal/resources/hazus.

Gately, D. 1974. "Sharing the gains from regional cooperation: A game theoretic application to planning investment in electric power." *Int. Econ. Rev.* 15 (1): 195–208.

Ghodsi, S. H., Z. Zahmatkesh, E. Goharian, R. Kerachian, and Z. Zhu. 2020. "Optimal design of low impact development practices in response to climate change." *J. Hydrol.* 580 (Jan): 124266. https://doi.org/10.1016/j.jhydrol.2019.124266.

Goharian, E., and S. J. Burian. 2018. "Developing an integrated framework to build a decision support tool for urban water management." *J. Hydroinf.* 20 (3): 708–727. https://doi.org/10.2166/hydro.2018.088.

Goharian, E., S. J. Burian, T. Bardsley, and C. Strong. 2016. "Incorporating potential severity into vulnerability assessment of water supply systems under climate change conditions." *J. Water Resour. Plann. Manage.* 142 (2): 04015051. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000579.

Hart, S. 2008. "Shapley value." In *The new Palgrave dictionary of economics*. London: Palgrave Macmillan.

Homer, C., J. Dewitz, L. Yang, S. Jin, P. Danielson, G. Xian, J. Coulston, N. Herold, J. Wickham, and K. Megown. 2015. "Completion of the 2011 national land cover database for the conterminous United States—Representing a decade of land cover change information." *Photogramm. Eng. Remote Sens.* 81 (5): 345–354.

Howe, G. M. 1950. "Map of drainage system Charleston S.C." Accessed September 1, 2023. https://www.charleston-sc.gov/DocumentCenter/View/5558/drainage1950?bidId=.

Hyun, J. Y., S. Y. Huang, Y. C. E. Yang, V. Tidwell, and J. Macknick. 2019. "Using a coupled agent-based modeling approach to analyze the role of risk perception in water management decisions." *Hydrol. Earth Syst. Sci.* 23 (5): 2261–2278. https://doi.org/10.5194/HESS-23-2261-2019.

Ichihara, K., and J. P. Cohen. 2010. "New York City property values: What is the impact of green roofs on rental pricing?" *Lett. Spatial Resour. Sci.* 4 (1): 21–30. https://doi.org/10.1007/S12076-010-0046-4.

IPCC (Intergovernmental Panel on Climate Change). 2014. "Climate change 2014: Synthesis report: Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change." Accessed September 1, 2023. http://www.ipcc.ch.

Jones, M. P., and W. F. Hunt. 2010. "Performance of rainwater harvesting systems in the southeastern United States." *Resour. Conserv. Recycl.* 54 (Aug): 623–629. https://doi.org/10.1016/j.resconrec.2009.11.002.

Just, R. E., and S. Netanyahu. 2004. "Implications of 'Victim Pays' infeasibilities for interconnected games with an illustration for aquifer sharing under unequal access costs." *Water Resour. Res.* 40 (5). https://doi.org/10.1029/2003WR002528.

Kilgour, D. M., A. Nishikori, and N. Okada. 1988. "Control regulation of water pollution: An analysis using game theory." *J. Environ. Manage.* 27 (2): 179–194.

Kim, J., J. Lee, Y. Song, H. Han, and J. Joo. 2018. "Modeling the runoff reduction effect of low impact development installations in an industrial area, South Korea." *Water* 10 (8): 968. https://doi.org/10.3390/w10080967.

Lawyer, C. 2022. *Coalitional game theory for stormwater management and Green infrastructure practices*. Columbia, SC: Univ. of South Carolina.

Loucks, D. P., and E. van Beek. 2017. "Water resources planning and management: An overview." In *Water resource systems planning and management*. Cham, Switzerland: Springer.

Macal, C. M., and M. J. North. 2010. "Tutorial on agent-based modelling and simulation." *J. Simul.* 4 (3): 151–162. https://doi.org/10.1057/jos.2010.3.

Macro, K., L. S. Matott, A. Rabideau, H. Ghodsi, and Z. Zhu. 2019. "OSTRICH-SWMM: A new multi-objective optimization tool for green infrastructure planning with SWMM." *Environ. Modell. Software* 113 (Mar): 42–47. https://doi.org/10.1016/j.envsoft.2018.12.004.

Madani, K. 2010. "Game theory and water resources." *J. Hydrol.* 381 (3–4): 225–238. https://doi.org/10.1016/j.jhydrol.2009.11.045.

Manson, S. M. 2001. "Calibration, verification, and validation." In *Proc., Meeting the Challenge of Complexity: Proc. of a Special Workshop on Land-Use/Land-Cover Change*, 42–46. Santa Barbara, CA: Center for Spatially Integrated Social Science at Univ. of California at Santa Barbara.

Michaelis, T., L. Brandimarte, M. Mazzoleni, S. Archfield, and S. Pande. 2020. "Capturing flood-risk dynamics with a coupled agent-based and hydraulic modelling framework." *Hydrol. Sci. J.* 65 (9): 1458–1473. https://doi.org/10.1080/02626667.2020.1750617.

Milly, P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer. 2008. "Stationarity is dead: Whither water management?" *Science* 319 (5863): 573–574. https://doi.org/10.1126/science.1151915.

Miquel, S., B. van Velzen, H. Hamers, and H. Norde. 2006. "Fixed tree games with multilocated players." *Netw. Int. J.* 47 (2): 93–101.

Molnar, C. 2022. "Shapley values." In *Interpretable machine learning: A guide for making black box models explainable*. 2nd ed. La Jolla, CA: International Machine Learning Society.

Montalto, F. A., T. A. Bartrand, A. M. Waldman, K. A. Travaline, C. H. Loomis, C. McAfee, J. M. Geldi, G. J. Riggall, and L. M. Boles. 2013. "Decentralised Green infrastructure: The importance of stakeholder behaviour in determining spatial and temporal outcomes." *Struct. Infrastruct. Eng.* 9 (12): 1187–1205. https://doi.org/10.1080/15732479.2012.671834.

Morris, J. T., and K. A. Renken. 2020. "Past, present, and future nuisance flooding on the Charleston peninsula." *PLoS One* 15 (9), https://doi.org/10.1371/journal.pone.0238770.

Multi-Resolution Land Characteristics Consortium. 2011. "National Land Cover Database 2011." Accessed September 1, 2023. https://www.mrlc.gov/data/legends/national-land-cover-database-2011-nlcd2011-legend.

Myerson, R. B. 1991. *Game theory: Analysis of conflict*. Cambridge, MA: Harvard University Press.

Niazi, M. A., and A. Hussain. 2012. *Cognitive agent-based computing–I: A unified framework for modeling complex adaptive systems using agent-based & complex network-based methods*. New York: Springer.

NOAA (National Oceanic and Atmospheric Administration). 2015. "Observed water levels at 8665530, Charleston, Cooper River Entrance SC." Tides & Currents. Accessed September 1, 2023. https://tidesandcurrents.noaa.gov/waterlevels.html?id=8665530.

NOAA (National Oceanic and Atmospheric Administration). 2016. "The historic South Carolina Floods of October 1-5, 2015." Accessed September 1, 2023. https://www.weather.gov/media/publications/assessments/SCFlooding_072216_Signed_Final.pdf.

NOAA (National Oceanic and Atmospheric Administration). 2021. "What percentage of the American population lives near the coast? Ocean facts." Accessed September 1, 2023. http://oceanservice.noaa.gov/facts/population.htmlv.

NOAA (National Oceanic and Atmospheric Administration). 2022. "Accessed September 1, 2023. U.S. coastline to see up to a foot of sea level rise by 2050." https://www.noaa.gov/news-release/us-coastline-to-see-up-to-foot-of-sea-level-rise-by-2050.

Parker, D. C., S. M. Manson, M. A. Janssen, M. J. Hoffmann, and P. Deadman. 2003. "Multi-agent systems for the simulation of land-use and land-cover change: A review." *Ann. Assoc. Am. Geogr.* 93 (2): 314–337. https://doi.org/10.1111/1467-8306.9302004.

Parrachino, I., A. Dinar, and F. Patrone. 2006. "Cooperative game theory and its application to natural, environmental, and water resource issues: 3. Application to water resources." In *Application to water resources (november 2006). World bank policy research working paper*, 4074. Amsterdam, Netherlands: Elsevier.

Patt, A., and B. Siebenhüner. 2005. "Agent based modeling and adaptation to climate change." *Q. J. Econ.* 74 (2): 310–320. https://doi.org/10.3790/vjh.74.2.310.

Peterson, B., and M. Porter. 2020. *Charleston and the South Carolina coast flooded record 89 times in 2019*. Charleston, SC: Post and Courier.

Platt, S. E. 2020. "Urban dialectics, misrememberings, and memory-work: The Halsey map of Charleston, South Carolina." *Int. J. Hist. Archaeol.* 24 (4): 989–1014. https://doi.org/10.1007/s10761-019-00533-8.

Qin, H. P., Z. Li, and G. Fu. 2013. "The effects of low impact development on urban flooding under different rainfall characteristics." *J. Environ. Manage.* 129 (Nov): 577–585. https://doi.org/10.1016/j.jenvman.2013.08.026.

Raei, E., M. Reza Alizadeh, M. Reza Nikoo, and J. Adamowski. 2019. "Multi-objective decision-making for green infrastructure planning (LID-BMPs) in urban storm water management under uncertainty." *J. Hydrol.* 579 (Dec): 124091. https://doi.org/10.1016/j.jhydrol.2019.124091.

Randall, M., J. Støvring, M. Henrichs, and M. B. Jensen. 2020. "Comparison of SWMM evaporation and discharge to in-field observations from lined permeable pavements." *Urban Water J.* 17 (6): 491–502. https://doi.org/10.1080/1573062X.2020.1776737.

Shapley, L. S. 1953. "Stochastic games." *Proc. Natl. Acad. Sci. USA* 39 (10): 1095–1100. https://doi.org/10.1073/pnas.39.10.1095.

Shoham, Y., and K. Leyton-Brown. 2008. *Multiagent systems: Algorithmic, game-theoretic, and logical foundations*. Cambridge, UK: Cambridge University Press.

Simpson, M. G. 2010. *Low impact development modeling to manage urban storm water runoff and restore predevelopment site hydrology*. Fort Collins, CO: Colorado State Univ.

Støvring, J., T. Dam, and M. B. Jensen. 2018. "Hydraulic performance of lined permeable pavement systems in the built environment." *Water* 10 (5): 587. https://doi.org/10.3390/w10050587.

Tanim, A. H., W. McKinnie, and E. Goharian. 2022. *Enhanced simulation of coastal compound flooding through fully-coupled modeling framework*. New York: Authorea Preprints.

Tank Depot. 2022a. "2000 Gallon plastic water storage tank." Accessed September 1, 2023. https://www.tank-depot.com/water-tanks/water-tanks-by-gallon-capacity/2000-gallon-water-tanks/.

Tank Depot. 2022b. "5000 Gallon Norwesco plastic potable water storage tank." Accessed September 1, 2023. https://www.tank-depot.com/water-tanks/water-tanks-by-gallon-capacity/5000-gallon-water-tanks/.

Tupper, J. A. 2012. *A cost comparison of a low impact development to traditional residential development along the South Carolina Coast*. Columbia, SC: Univ. of South Carolina.

Ureta, J., M. Motallebi, A. E. Scaroni, S. Lovelace, and J. C. Ureta. 2021. "Understanding the public's behavior in adopting green stormwater infrastructure." *Sustainable Cities Soc.* 69 (Jun): 102815. https://doi.org/10.1016/j.scs.2021.102815.

US Global Change Research Program. 2017. "Summary findings of the fourth national climate assessment." Accessed September 1, 2023. https://nca2018.globalchange.gov/.

Van De Meene, S. J., R. R. Brown, and M. A. Farrelly. 2009. "Exploring sustainable urban water governance: A case study of institutional capacity." *Water Sci. Technol.* 59 (10): 1921–1928. https://doi.org/10.2166/wst.2009.190.

Voicu, I., and V. Been. 2008. "The effect of community gardens on neighboring property values." *Real Estate Econ.* 36 (2): 241–283. https://doi.org/10.1111/j.1540-6229.2008.00213.x.

Von Neumann, J., and O. Morgenstern. 1944. *Theory of games and economic behavior*. Princeton, NJ: Princeton University Press.

Wagenaar, D. J. 2012. *The significance of flood duration for flood damage assessment*. Delft, Netherlands: Delft Univ. of Technology.

Wang, M., D. Zhang, S. Lou, Q. Hou, Y. Liu, Y. Cheng, J. Qi, and S. K. Tan. 2019. "Assessing hydrological effects of bioretention cells for urban stormwater runoff in response to climatic changes." *Water* 11 (5): 1–20. https://doi.org/10.3390/w11050997.

Wayfair. 2022. "60 Gallons Gal: Weather resistant plastic drainable dual overflow planter rain barrel." https://www.wayfair.com/storage-organization/pdp/60-gal-weather-resistan-plastic-drainable-rain-barrel-tgrb1002.html.

Weather Underground. 2015. "Charleston AFB, SC weather history." Weather Underground. Accessed September 1, 2023. https://www.wunderground.com/history/daily/us/sc/charleston-air-force-base/KCHS/date/2015-10-1.

William, R., J. Garg, and A. S. Stillwell. 2017. "A game theory analysis of green infrastructure stormwater management policies." *Water Resour. Res.* 53 (9): 8003–8019. https://doi.org/10.1002/2017WR021024.

William, R., A. Goodwell, M. Richardson, P. V. V. Le, P. Kumar, and A. S. Stillwell. 2016. "An environmental cost-benefit analysis of alternative green roofing strategies." *Ecol. Eng*. 95 (Oct): 1–9. https://doi.org/10.1016/j.ecoleng.2016.06.091.

Williams, E., and T. Moore. 2020. "Rising tides take Charleston to the brim, threatening businesses." *The Post and Courier*, October 19, 2020.

Xu, T., H. Jia, Z. Wang, X. Mao, and C. Xu. 2017. "SWMM-based methodology for block-scale LID-BMPs planning based on site-scale multi-objective optimization: A case study in Tianjin." *Front. Environ. Sci. Eng.* 11 (Apr): 1–12. https://doi.org/10.1007/s11783-017-0934-6.

Yang, L. E., J. Scheffran, D. Süsser, R. Dawson, and Y. D. Chen. 2018. "Assessment of flood losses with household responses: Agent-based simulation in an urban catchment area." *Environ. Model. Assess.* 23 (4): 369–388. https://doi.org/10.1007/s10666-018-9597-3.

York, C., E. Goharian, and S. J. Burian. 2015. "Impacts of large-scale stormwater green infrastructure implementation and climate variability on receiving water response in the Salt Lake City area." *Am. J. Environ. Sci.* 11 (4): 278–292. https://doi.org/10.3844/ajessp.2015.278.292.

Zahmatkesh, Z., J. B. Steven, M. Karamouz, H. Tavakol-Davani, and E. Goharian. 2014. "Low-impact development practices to mitigate climate change effects on urban stormwater runoff: Case study of New York City." *J. Irrig. Drain.* 14 (1): 04014043. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000770.

Zhang, S., and Y. Guo. 2014. "SWMM simulation of the storm water volume control performance of permeable pavement systems." *J. Hydraul. Eng.* 20 (8): 06014010. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001092.