Nature-based Solutions at the Interface of Hydro-Environmental Science, Social Justice, and Complex Decision-making

by
Cynthia (Cyndi) Vail Castro

A Dissertation submitted to the Department of Civil & Environmental Engineering,
Cullen College of Engineering
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in Civil Engineering

Chair of Committee: Keh-Han Wang

Committee Member: Hyongki Lee

Committee Member: Cumaraswamy Vipulanandan

Committee Member: Hong-Yi Li

Committee Member: Murugesu Sivapalan

University of Houston
December 2021

DEDICATION

This dissertation is dedicated to Noah. You are forever my sunshine. Being able to witness how your untethered essence interacts with this world, you have inspired this research for your generation and those to follow. You have been with me from the beginning, and I am refreshed and strengthened by your joy and intrinsic wonder. Thank you for simply being you.

ACKNOWLEDGMENTS

My purpose in returning to academia was to be involved in climate adaptation and mitigation strategies through novel research in a manner that would directly benefit people. The prospect to work locally provided several unique opportunities for engaging with key decision-makers, including the resilience team at the City of Houston. I would like to thank both my current advisor, Dr. Keh-Han Wang, and my former advisor, Dr. Hanadi Rifai, for taking time to share advice and resources toward the success of this research. I also thank the other members of my committee for sharing constructive comments and providing alternative points of view. Sincere thanks are extended to Dr. Murugesu Sivapalan for humoring my many inquiries and casting a vision that is both challenging and inspiring. I look forward to working with you during the postdoc.

Importantly, I thank the support of my family and friends. Thanks to my chosen sister, Aimee, for always being my person. I am grateful to my mom for showing me what it means to be strong. Thank you to my spouse, Adrian, for being an example of how to pursue important life goals with sincerity. Thank you for your character, for your many provisions, and for your inspiration. I thank my son, Noah, who has been my constant strength throughout this process. In your brief time on earth, you have revealed an entirely new meaning of goodness. I hope to make you proud and to be a small part of improving this world toward justice and beauty. I also thank my funding agencies, as this research was only possible through the National Science Foundation Graduate Research Fellowship Program (NSF-GRFP) Award No. 2013162199 and the National Science Foundation INTERN Fellowship Award No. 1934192.

ABSTRACT

One of the greatest threats facing civilization is climate change and the associated impacts to biodiversity, hydro-meteorological hazards, environmental degradation, and social vulnerability. We have the opportunity to mitigate such negative effects by embracing the restorative power of nature and strategically incorporating natural systems within the built environment. Nature-based solutions (NBSs) encompass various types of green infrastructure, which combine earthen and engineered materials, to reduce the flow of stormwater and capture pollutants at the source of collection. By increasing greenspace within the built environment, NBSs also store carbon emissions, improve societal well-being, and restore ecosystem health. However, NBSs have not reached their full potential due to an inadequate understanding of how hydro-environmental dynamics and social characteristics interrelate within the overall system, particularly at the level of human activity and urban planning (i.e., the watershed-scale). Moreover, NBS implementation has been constrained due to elusive institutional and societal barriers that have yet to be fully understood and positioned within actionable policy frameworks. The challenges facing NBS adoption are not purely qualitative nor quantitative, as they exist at an interface between the social and physical sciences. Historically, much of the work involving human-water systems has been conducted in rural environments, due in part to challenges of urban stormwater modeling. In order to foster sustainable solutions within the built environment, we must extend our systems-thinking approaches to thoroughly entangle one of the most complex systems available: the flood-prone metropolis. As such, this study amalgamates hydro-environmental science, social justice, and complex decision-making using intersectoral approaches to strengthen NBS adoption within the urban environment.

Specifically, this study bridges disciplinary divides to 1) advance NBS policy-making using stakeholder cognition and properties of network theory, 2) address overlapping NBS functionalities by developing a novel spatial data infrastructure system for the entire contiguous United States, and 3) optimize NBS planning at the watershed-scale by balancing economic, environmental, and social characteristics. NBSs are investigated as a holistic human-environmental system with many vantage points for analysis, thereby eliciting novel causal connections across institutional and spatial planning scales.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

ADI	Area Deprivation Index
AJAX	Asynchronous JavaScript and XML
API	Application programming interface
BGI	Blue-green infrastructure
BMP	Best management practices
CDC	Centers for Disease Control
CHANS	Coupled human and natural systems
CLD	Causal loop diagrams
CN	Curve Number
CONUS	Contiguous United States
CRED	Center for Research on the Epidemiology of Disasters
DIKIW	Data, information, knowledge, intelligence, wisdom
EPA	Environmental Protection Agency
Esri	Environmental Systems Research Institute
FCM	Fuzzy cognitive mapping
FEMA	Federal Emergency Management Agency
GISP	Green Infrastructure Spatial Planning
GIFP	Green Infrastructure Focus Planning
GMB	Group model building
GI	Green infrastructure
GIS	Geospatial information system
HEC-HMS	Hydrologic Engineering Center's Hydraulic Modeling System
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
LID	Low-impact development
MCDA	Multiple criteria decision analysis
NASA	National Aeronautics & Space Administration
NBS	Nature-based solutions

NCAR	National Center for Atmospheric Research
NLCD	National Land Cover Database
NOAA	National Oceanic and Atmospheric Administration
NRCS	United States Natural Resources Conservation Service
NSDI	National spatial data infrastructure
NSGA	Nondominated Sorting Genetic Algorithm
OGC	Open Geospatial Consortium
PCSWMM	Personal Computer Storm Water Management Model
PSS	Planning support system
REST	Representational state transfer
SAOT	Spatial allocation optimization tool
SDM	System dynamics modeling
SFD	Stock-and-flow diagram
SSURGO	Soil Survey Geographic Database
ST	Screening tool
SuDs	Sustainable urban drainage systems
SUSTAIN	System for Urban Stormwater Treatment and Analysis Integration
SVI	Social Vulnerability Index
SWMM	Storm Water Management Model
TPL	Trust for Public Land
UN	United Nations
UNEP	United Nations Environment Programme
UNISDR	United Nations International Strategy for Disaster Reduction
URL	Uniform resource locator
USACE	United States Army Corps of Engineers
USDA	United States Department of Agriculture
USGS	United States Geological Survey
WEF	Water-energy-food
WSUD	Water-sensitive urban design

1. INTRODUCTION

1.1 Overview

Flooding is the most prevalent and influential natural disaster in the world, causing more economic damage and affecting more people than any other natural event (UNISDR and CRED, 2015). Water processes are subject to stressors from intensified climate change and human development patterns, with over two-thirds of the global population projected to reside in urban areas by 2050 (United Nations, 2018). Climate change and urban densification increase flood risk exponentially while also threatening biodiversity, environmental degradation, and social vulnerability (Huong and Pathirana, 2013; Semadeni-Davies et al., 2008), thereby urging policy makers and scientists to transition toward innovative flood mitigation measures that address cross-cutting themes (Demuzere et al., 2014; Golden and Hoghooghi, 2018). Moreover, the era of the Anthropocene has highlighted the profound impact of human activity on the biosphere and has suggested a complete transformation of water science by including humans as an endogenous component of the watershed system (Vörösmarty et al., 2013).

Traditional stormwater networks, known as greywater infrastructure, are typically comprised of concrete and metal conveyance systems that transport rainfall offsite and into bodies of water. Such infrastructure is often designed to accommodate existing conditions, which may quickly become obsolete. Conversely, nature-based drainage solutions strategically incorporate natural materials, such as vegetation and soil, into the urban fabric to slow the course of stormwater flow through on-site evaporation and infiltration (Demuzere et al., 2014). Nature-based solutions (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). Common NBSs include rain gardens, green roofs, retention ponds, bioswales, water cisterns, and permeable pavements, which operate collectively to mitigate stormwater volume by improving infiltration capacity (Ruangpan et al., 2020). In addition to mitigating stormwater, NBSs have been associated with improved mental and physical health, social vulnerability, crime rates, and economic prosperity through enhanced levels of greenspace (Bowen et al., 2014; Bratman et al., 2019; Hansen et al., 2019). NBSs provide environmental benefits through abatement of urban heat levels, air and water quality, noise pollution, and greenhouse gasses (Anderson and Gough, 2020; Berardi et al., 2014; van den Bosch and Ode Sang, 2017). Moreover, NBSs contribute to conservation efforts by enhancing ecosystem diversity and connectivity (Keesstra et al., 2018). The United Nations (UN) has deemed NBSs as an essential component toward achieving the goals of the Paris Climate Agreement, providing up to one-third the necessary carbon emissions' reduction by 2030, thereby declaring an NBS Climate Manifesto to scale-up NBS adoption globally in upcoming years (UN Environment Programme, 2019).

At the local scale (i.e., laboratory-, plot-, neighborhood-scale), NBS technologies have shown great promise in addressing both stormwater abatement goals and environmental restoration (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). The hydrological literature has suggested that NBSs, interacting with human processes, operate as a complex system with overlapping social and physical properties (Giacomoni and Zechman, 2010; Kuller et al., 2017). We know that the location of human settlements can influence social factors that have been linked to NBS placement, such as improvements in communal well-being, mental health, recreation, and physical health (Alves et al., 2019; Fenner, 2017; H. Li et al., 2017). When planning for the overlapping co-benefits of NBS systems, there will exist inherent tradeoffs between spatial priority and functionality that must be considered in an optimization scheme.

By focusing on drainage characteristics, however, NBS planning often promotes stormwater abatement while assuming additional co-benefits will somehow propagate naturally throughout the system. NBS systems are typically planned with either simplified data-overlay methods for defining hot-spots of vulnerable locations or complex hydro-dynamic programs that prioritize stormwater 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, many NBS plans have tended to neglect the social dimension altogether in favor of Earth-system processes, thereby lacking optimal configurations for capturing the full scope of available co-benefits (Kandakoglu et al., 2019).

We thereby have substantial knowledge gaps regarding informed NBS planning (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). In this way, NBS multifunctionalities are not included as an explicit representation of their locational benefits, thus limiting the maximum potential of NBSs to mitigate cross-cutting issues within the urban fabric. 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 improvements (Golden and Hoghooghi, 2018; Madureira and Andresen, 2014). To fully capture the multifunctionalities of NBS systems and improve implementation, we necessitate holistic frameworks encompassing the variety of physical and social functionalities associated with NBSs, which is a fertile area of research.

In addition to a lack of social representation within NBS planning frameworks, the decision to implement NBSs within a given locale is also highly dependent on complex 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. 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 support is essential for achieving widespread NBS adoption. Observational case studies have identified several key challenges to NBS uptake, including public perception (Baptiste et al., 2015), local culture (Derkzen et al., 2017), institutional frameworks (Solheim et al., 2021), and technical roles (Zuniga-Teran et al., 2020). While these barriers have been studied as isolated events, we lack an understanding of how such factors operate holistically and influence one another. When human actors interact with NBS systems through planning and group behavior,

social and political constructs adapt to the new environment, which further refines local values and drives emergent phenomena. Each cycle of this complex system denotes an additional human-NBS response, which must be assessed according to altered characteristics. Therefore, we cannot mitigate the system by simply assigning policies that resolve select barriers and assume the results will be proportionally related. Instead, we must be able to incorporate human agency as an endogenous component that influences and co-evolves with the physical systems they seek to shape. For this, we require the coupling of human behavior with NBS responses, which may be accomplished through a holistic application of systems-thinking. Studies have also shown that attitudes regarding NBSs are improved when stakeholders can visualize and 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 decision-makers are able to identify and prioritize the multiple co-benefits involved in the NBS system, and to do so in an intuitive manner.

The merging of Newtonian processes, such as infiltration or pollutant load runoff, with the Darwinian processes of social behavior will help us bridge the gaps between NBS research, design, politics, community acceptance, and management. 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 watersheds 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. Such integration from the social sciences might include considering the following variables in our planning paradigms: governance patterns, monitoring programs, financial aptitude, action plans, citizen involvement, and the general health and well-being of society (Kabisch et al., 2016). Enhanced integration of environmental phenomena, such as ecosystem services, pollutant dispersion, and sediment transportation, into hydrological models is an area of ongoing research (Grineski et al., 2015; Szewrański et al., 2018). 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). A workshop conducted by the UN Environmental Programme (UNEP) Intergovernmental Panel on Climate Change (IPCC) revealed that complex policy-making and social dynamics are the primary impediments to NBS uptake and recommended co-produced knowledge between practitioners and researchers to overcome implementation challenges (Frantzeskaki et al., 2019).

In addressing such issues, increased emphasis is being placed on information-based science coupled with cognitive, systems-based modeling to explore connections between human behavior and the environment. Instead of relying solely on empirical theories about how catchments operate, we are trending toward rigorous hypothesis testing by learning from a combination of qualitative and quantitative models to better understand the rationale behind widespread socio-environmental phenomena (Konar et al., 2019). There now exists

opportunity to recast issues of catchment-scale NBS phenomena into a data-driven framework using real-world sites, stakeholders, hydro-dynamic models, and geospatial observations (Gaál et al., 2012; Peters-Lidard et al., 2017; Rakovec et al., 2016).

To bridge this gap, three novel information-based frameworks are derived and investigated to improve our understanding of NBS phenomena. Specifically, stakeholder group-building and systems-thinking are used to define and relate institutional feedbacks associated with NBS systems and to explore policy coherence among disparate management strategies. A geospatial repository and data information system is derived to link decision-makers, resiliency stakeholders, planners, and researchers with a vast, curated suite of multifunctional datasets associated with NBSs. Moreover, spatial properties of social health and vulnerability are integrated into a comprehensive optimization scheme for NBS planning at the watershed-scale according to transdisciplinary characteristics of social equity, economic efficacy, environmental pollutant load reduction, and stormwater volume abatement.

1.2 Research Objectives

1. **Identify areas of policy synergy and conflict among NBS management strategies.** Numerous barriers to NBS adoption have been identified as stemming from human behavior, yet we lack an understanding of how such factors interrelate to inform policy design. The identification of synergies and trade-offs among diverse management strategies is necessary to generate optimal results from limited institutional resources. The aim of this research objective is to define and assess a novel framework for identifying areas of policy coherence from stakeholder collaboration and unique properties of network theory. This framework is demonstrated through a case study of NBS policy-making and socio-institutional feedbacks in Houston, Texas, USA.

2. **Develop a national data system for improved visualization of NBS co-benefits.**

Comprehensive datasets for nature-based solutions (NBS) and their diverse relationships have not been accumulated into a deployable format. This research gathers and integrates geospatial datasets from the social, ecological, environmental, and hydrologic domains using seamless, cloud-based data services for the contiguous United States (CONUS). Decision-making and research are enhanced by assimilating web-based datasets into a user-friendly sustainability tool that amalgamates quantitative watershed datasets with qualitative social co-benefits and climatic conditions. This spatial system serves to foster participatory planning capabilities and integrate local sustainability goals into decision-support frameworks. Such a platform strengthens the knowledge base necessary for addressing multiple, co-evolving issues of societal relevance, an essential component of fully espousing NBSs within the realm of socio-technological systems.

3. **Optimize spatial allocation by combining social equity with hydro-dynamics.**

NBSs have been shown to improve social equity through enhanced physical health (e.g., heart disease, diabetes), mental health (e.g., post-traumatic stress disorder, depression), aesthetics, property values, recreational opportunities, community meeting spaces, cleaner air, and general societal well-being. However, current optimization frameworks for NBSs rely on stormwater quantity abatement and, to a lesser extent, economic costs and environmental pollutant mitigation. This research objective explores how strategic management strategies associated with NBS planning may be optimized while considering the tripartite interactions between water, environment, and social co-benefits. A large-scale NBS watershed is calibrated using standard hydro-environmental modeling and optimized on the basis of stormwater abatement, pollutant load reduction, and economic efficacy. The

resulting spatial allocation is integrated with properties of social equity through a novel framework involving the Area Deprivation Index (ADI) and the Gini coefficient. By embedding social equity into the fabric of the NBS planning process, social justice is improved within a balanced system.

2. STATE OF KNOWLEDGE

2.1 Systems-based Paradigms in Hydrology

The emergent field of socio-hydrology was established to study the evolution of interactions between water and society as a linked system (Sivapalan et al., 2012), whereby all watershed processes contain an inherent two-way feedback between impacting humans and being impacted by humans (Konar et al., 2019). The premise of socio-hydrology is that human agencies are endogenous factors that influence and co-evolve with the water systems they seek to shape. Instead of attempting to super-impose human dynamics on the results of physical models or as a pre-existing boundary condition, we are transitioning toward modeling frameworks that integrate human logic as a stimulus to interact with the environment and reveal emergent phenomena (Bouziotas and Ertsen, 2017). Socio-hydrology relies heavily on the concept of system dynamics modeling (SDM), which simulate processes within a complex system according to a set of interrelated dynamical equations (Allen, 1988). Systems dynamic models are not designed for predictive purposes but instead are intended to provide insight into the feedbacks involved in complex issues.

These concepts have been widely applied to hydrological issues of water-use, drought, and flooding (Di Baldassarre et al., 2019, 2015; Pande and Sivapalan, 2017) with significantly less attention throughout the NBS literature (Ruangpan et al., 2020; Schifman et al., 2017). While there have been numerous attempts to study the co-benefits that ensue from NBSs, there exists a limited understanding of how social phenomena directly impacts NBS adoption. In order to shift stormwater management regimes away from sole reliance on greywater infrastructure, we require an improved understanding of NBSs as a coupled human-water system. In addressing this gap, the broad domain of systems-thinking is a

useful paradigm for eliciting the role of society embedded within complex NBS phenomena. SDMs are one sub-component of systems-thinking, however, the systems theory extends far beyond formal dynamical models.

2.1.1 The Systems-thinking Process

The systems-thinking process involves a series of phases, often performed in sync with modelers and stakeholders, to understand how complex systems operate. These phases (i.e., dynamic-thinking, causal-thinking, feedback-thinking, and strategy-thinking) are depicted in **Fig. 1** (loosely adapted from Kim et al. (2017)) and described in terms of the common phenomena they seek to address. The premise of systems-thinking is that complex issues can be better understood when the individual components of the system are identified and the causal links between them are associated (Allen, 1988). The initial stages of systems-thinking include 1) Group Model Building (GMB), which is used to derive a community understanding of the dynamic problem and associated variables through stakeholder interactions (e.g., workshops, interviews), and 2) Causal Loop Diagrams (CLD), which are simplified graphical representations of the stakeholder-defined variables and their interactions that form feedbacks (Forrester, 1994). These feedbacks may connect to form closed loops, which define the system trajectory as either balancing (i.e., trending toward equilibrium) or reinforcing (i.e., propagating change) (Sternam, 2002). Large causal systems are often too convoluted for practical inference of policy implications from a visual analysis alone, due to the many interactive feedbacks within the system (Bureš, 2017; Osoba and Kosko, 2019). System dynamics modeling (SDM) is the translation of these complex feedbacks into a quantified model to simulate the associated dynamics, which may be used to test unique hypotheses for robust decision-making (Richmond, 1993). A common SDM technique is a stock-and-flow diagram (SFD), which simulates

accumulations and changes within the system through a set of integral equations. SFD models require numerical descriptions of system performance over time, which are not often available when considering novel policies and the dynamics of human behavior (Bureš et al., 2020). An alternative to SDM is fuzzy cognitive mapping (FCM), which combines the strengths of stakeholder knowledge with network theory to produce semi-quantitative scenarios of system change.

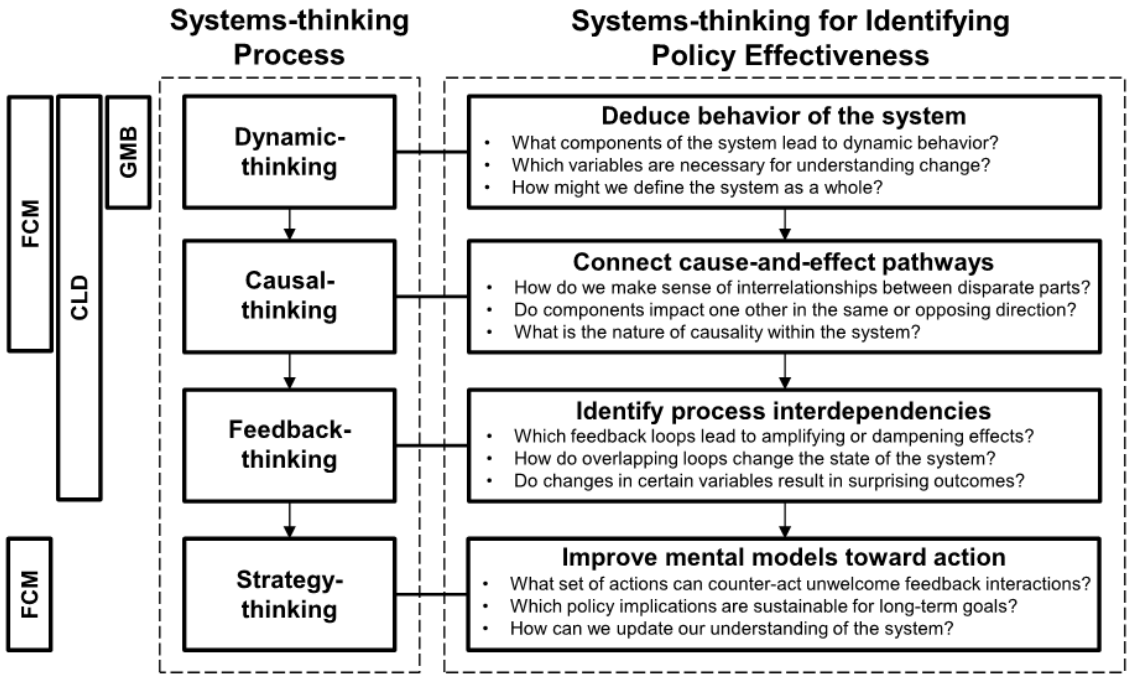

Fig. 1. Framework of holistic systems-thinking for identifying policy coherence.

There have been calls within the literature to more clearly identify policy effects from dynamic systems by exploring the causal loops underlying the system structure and simulating their resulting behaviors (de Gooyert et al., 2016). Feedbacks and adaptations amongst complex human-environmental systems must be understood and explicitly accounted for in order to optimize system-wide sustainability with limited resources. To address this gap, this research proposes a thorough integration of qualitative and semi-quantitative systems-based approaches, which are further described in **Section 2.1.1.1**, to

reveal policy-oriented relationships that would not be clear from causal logic alone, but which also do not require the complex numerical modeling associated with SFDs.

2.1.1.1 *Group Model Building*

Group model building is a stylized approach for eliciting complex system components and their inter-relationships from stakeholder knowledge (Vennix, 1999). GMB emphasizes capacitance building for framing and visualizing the problem, identifying potential leverage points, analyzing policies, and designing effective solutions within dynamical systems. GMB highlights the problem-structuring process, rather than the end-goal of a simulation model, to form a dynamic hypothesis of how the system operates through real-world experiences shared by a collective group. Common GMB techniques include behavioral simulations, role playing games, stakeholder workshops, white board sketches, and curated interviews (Pahl-Wostl, 2007). Such processes are often facilitated through the use of scripts, which were spawned by Andersen and Richardson's (1997) call to strengthen the scientific basis of GMB by thoroughly documenting the techniques used in community modeling. The scripts are typically intended for live workshops and encompass a range of topics, including GMB preparation (stakeholder selection, room logistics, scheduling), group interaction (complex-thinking skills, hopes and fears), causal loop modeling (variables, causal relationships, dynamic structure), and follow-up (model review, reflection, feedback, action) (Hovmand et al., 2011).

When confronted with a complex system comprising many interacting components, humans typically try to reduce the problem complexity by rationalizing simplified connections, thereby misperceiving the feedback structure of the system. Such inability to identify the dynamics of a complex system often results in missed opportunities or unintended consequences from well-intended interventions (Sterman, 2001). The mental

models held by humans describe an internal representation of a real system as shaped by interacting social actors within the environment, including their cognitive biases, values and goals, which have been derived from lived experiences (Jones et al., 2011). By elucidating such mental models through structured protocols, we are better positioned to evoke the dynamic relationships necessary for sound decision-making.

GMB has been widely used within the environmental sciences to support stakeholders in identifying information feedbacks and empowering a diversity of cross-sectoral voices in policy-making (e.g., Butler and Adamowski (2015), Stave (2002)). In addressing issues of water management, GMB has been used to foster an understanding of long-term effects resulting from interventions to river basins and urban water systems (Winz et al., 2009). GMB has also been demonstrated as a useful tool for exploring the implications of climate change in water resources planning (Langsdale et al., 2009). Moreover, GMB has been used as a diagnostic tool to develop indicator frameworks for integrated management strategies (Vugteveen et al., 2015). GMB exercises have been demonstrated to positively support communication of complex system dynamics with decision-makers and to facilitate visualization of causal feedbacks (Scott et al., 2016). Stakeholder-led models allow us to define the co-evolution of environmental phenomena, as impacted by social norms and beliefs, when such relationships would otherwise elude formal definition.

2.1.1.2 Causal Loop Diagrams

A primary step involved in systems dynamic modeling includes forming dynamic hypothesis about how the system functions through CLDs to showcase relationships between variables (Sternam, 2002). In CLD diagrams, individual links are marked as positive (+), such that related variables change in the same direction, or negative (-), where a change in one variable has the opposite impact on the linked variable. The feedbacks

within the CLD are described as balancing loops (an odd number of negative links) or reinforcing loops (an even number of negative links). Reinforcing loops indicate that an effect of variation within individual variables propagates throughout the loop and causes rapid change within the system through growth or decline. Balancing loops counteract change and trend the system toward equilibrium (Sternam, 2002).

This methodology is useful for demonstrating how feedbacks between rapidly changing infrastructure decisions and co-evolving social phenomena may be visualized at a general level through causal relationships, thereby elucidating new knowledge between disparate phenomena. CLD models have been noted as beneficial tools within socio-hydrological investigations because they (Inam et al., 2015; Kotir et al., 2017; Zare et al., 2019):

- ✓ Represent and simplify complex interactions,
- ✓ Identify key hydrologic, social, economic, and institutional drivers,
- ✓ Assess long-term impacts of dynamic factors and how they are related,
- ✓ Suggest how policy changes will impact the system at the regional scale,
- ✓ Examine the future of systems within existing social constructs,
- ✓ Provide a visual interpretation of complex systems for holistic planning,
- ✓ Facilitate participation of system stakeholders and sharing of information, and
- ✓ Prioritize components that require additional in-depth studies.

CLDs are conceptual in nature and are intended to increase a holistic understanding of the water resources system for improved management. The resulting model is cyclical, rather than linear, and explains non-linear behavior within the catchment in terms of critical socioeconomic, policy, and institutional processes. Feedback loops are formed that integrate key drivers to explain the resulting variability in the hydrologic response, which is of paramount importance for understanding how the system behavior is governed. The dominant loops within the resulting CLD inform management where key leverage points

are located and what types of action would result in the system equalizing or changing exponentially. Institutional changes focused on such leverage points improve the balance within the feedback loops and increase overall efficacy of the coupled human-water system.

2.1.1.3 Fuzzy-cognitive Maps

While CLD's provide information regarding the direction and central relationships of the system, an understanding of how the system will play out dynamically over time is necessary for decision-making. For this, fuzzy cognitive maps provide a semi-quantitative basis for simulating complex dynamics according to the system structure and the strengths of variable relationships. FCMs were first proposed by Kosko (1986) for quickly simulating the dynamics of complex causal maps. FCM theory is based on a pseudo combination of cognitive mapping (Axelrod, 1976), fuzzy logic (Zadeh, 1975), semantic networks (Richens, 1956), and neutral networks (McCulloch and Pitts, 1943) for representing systems with a high degree of uncertainty by leveraging stakeholder knowledge (Glykas, 2005). Cognitive mapping is a means for capturing the subjective knowledge of individuals, which fosters systems-thinking and awareness of internal assumptions regarding how a system operates. According to the structure of the causal map, FCMs are represented by fuzzy directed diagraphs, which describe the feedback linkages between variables as a set of neural processing units, each with signed and weighted properties (Nápoles et al., 2018). As human behaviors, tendencies, and feelings are difficult to measure empirically, FCMs provide a systems-based approach to numerically depict and simulate abstract concepts by identifying the strengths between variables without necessitating robust datasets over time.

FCMs represent indirect causality by structuring and parameterizing CLDs according to fuzzy logic from group beliefs, which are defined as a numerical representation of qualitative strengths (e.g., low, medium high) between variables, typically using weighted edges between -1 (strong negative causality) and +1 (strong positive causality) (Gray et al., 2014). Mathematical pairwise associations are then summarized within a square adjacency matrix, which may be simulated to better understand current and projected system states (Özesmi and Özesmi, 2004). According to Henly-Shepard et al. (2015), FCMs are popular for assessing the dynamics of socio-ecological systems but are not often used to iteratively measure conceptual change for stakeholder-derived assessment of unique policy changes and holistic planning within the system. Effective policy design necessitates understanding how system variable changes will result in alterations to specific state vectors, which may fail if the modeler or planner does not consider the causal chain(s) driving the policy effects. As such, the mechanistic nature of FCMs is beneficial to identify such causal chains and improve choosing the most effective policy design amongst many options (Capano and Howlett, 2019). Such modeling provides a roadmap for policy-making whereby future changes within the system are simulated and compared to a base-line scenario to better understand how specific variables influence the overall system dynamics.

To calculate the FCM network, the variables within the system are denoted as equivalent to neurons that can be turned “on” (where variables are clamped to a state vector value of +1) or “off” (where variables are set to a state vector value of 0) during simulation while also adopting in-between states (i.e., “fuzzy” states). A value of +1 indicates the variable is strengthened to the maximum possible weight at the beginning of the simulation, thereby influencing all connecting feedbacks, while a clamped value of 0 means the

variable does not change at the system on-set and rather is only influenced by causal connections within the system. In other words, if a variable is "activated" for the system simulation, the vector state of that variable is represented as a neuron that fires and impacts all variables that are causally dependent upon it. The activated variable state is multiplied by the entire adjacency matrix at each time step, which may then alter the state vector values of non-activated concepts (Jetter and Schweinfort, 2011). The multiplication rules are chosen according to a threshold function (e.g., bivalent, trivalent, sigmoid, hyperbolic tangent, step-wise, linear) describing when the system should stop iterating upon reaching equilibrium, further described by Bueno and Salmeron (2009) and Tsadiras (2008). The extent to which the "off" variables are altered throughout the simulation depend on the direction of causal feedbacks and their strengths, which may in turn activate other system variables, thereby spreading in a non-linear fashion until the system reaches equilibrium.

When applied to policy-making, a series of artificial scenarios are simulated by activating unique policy variables and comparing the end-state vectors against a baseline model, where all variables are simulated in the "off" position. The extent of change between the activated and the baseline scenario projects how the system will respond to unique policies according to causal interactions throughout the entire model.

2.1.2 Systems-based Research in the NBS Literature

Several state-of-the-art reviews have highlighted a rise in systems-thinking approaches within the fields of sustainability, water resources, environmental science, and hydrology (Mashaly and Fernald, 2020; Moon, 2017; Turner et al., 2016; Zomorodian et al., 2018). Researchers have incorporated systems modeling in various human-water applications to identify complex causal relationships and co-evolving feedbacks in the planning of water supply and demand (House-Peters and Chang, 2011), river basin management, flooding

(Ahmad and Simonovic, 2015; Perrone et al., 2020), and irrigation (Pluchinotta et al., 2018; Saysel et al., 2002). System thinking approaches have proliferated in the management of hydro-environmental systems, due in large part to pressing challenges associated with urbanization and climate change (Turner et al., 2016). These studies describe the dynamic complexities associated with water resources management and how to account for their feedbacks when planning systems that will impact society (Mirchi et al., 2012). Such studies have shown that systems modeling is an effective tool for describing the linkages between social phenomena and physically-based hydrological processes (Blair and Buytaert, 2016; Fernald et al., 2012; Kotir et al., 2017; Zomorodian et al., 2018).

Research has begun to emerge where systems-thinking has been applied to NBSs to facilitate an understanding of overlapping co-benefits and to promote stakeholder involvement (Coletta et al., 2021; Giordano et al., 2020; Gómez Martín et al., 2020; Pagano et al., 2019; Santoro et al., 2019). Many of these studies have applied dynamic- and causal-thinking to define the nature of complex human-environmental systems (Mashaly and Fernald, 2020). Some studies have also explored alternative management strategies through FCM-based scenarios (e.g., Giordano et al., 2020; Gómez Martín et al., 2020; Kokkinos et al., 2020) and SFD models (e.g., Kotir et al., 2016; Pagano et al., 2019; Sušnik et al., 2012). Additional research has applied feedback-thinking to characterize system behavior into archetypes, which are typically described with storylines and narratives (e.g., Bahri, 2020; Gebrai et al., 2021). These studies operate under the assumption that dominant feedback loops within the system may be used to inform management of key leverage points and to facilitate which types of action would result in optimal results. Such research has been useful in demonstrating the potential for systems-

thinking to facilitate an understanding of NBS benefits and tradeoffs regarding institutional policies and stakeholder perceptions.

2.1.3 The Need for Integrated Approaches

Previous studies have typically focused on investigating the effectiveness of NBS management through increased stakeholder involvement (Gómez Martín et al., 2020) rather than a baseline understanding of how social characteristics impact NBS phenomena as a holistic system (Ruangpan et al., 2020). Systems-based research within the NBS literature has generally considered the effect of different environmental phenomena on NBS system performance (e.g., land use change, climate change, co-benefits production), with lesser attention to specific management strategies. Studies that have applied systems-thinking to policy design have relied on a visual assessment of complex CLD feedback loops by describing their interactions through a lengthy narrative or story-line (e.g., Collins et al., 2013; Paterson and Holden, 2019; Stepp et al., 2009). Given the large magnitude of many causal systems, such manual interpretations are often impractical.

For example, Brennan et al. (2015) applied a systems-thinking approach to better understand how various policies could impact social health across a large community. This study resulted in 50 unique CLDs with an astounding 1555 feedback loops. To derive useful insights from the data, the 50 CLDs were synthesized into one composite diagram using the variables that were consistently identified by 20% of the stakeholders. In such an approach, it could be argued that much of the causal richness is lost when ~80% of the variables proposed by the community are discarded. Aggregation of causal relationships to aid human understanding is a common necessity within system dynamics (Ryan et al., 2021), especially considering the limitation of reliable datasets for robust model quantification (e.g., SFDs) (Mirchi et al., 2012). However, when informing policy

strategies for complex systems, some fashion of quantitative modeling is necessary to adequately capture the many causal interactions and their dynamic behaviors.

FCM-based scenarios for evaluating policies have tended to highlight the strengths of individual variables toward system goals with lesser discussion of how the internal feedback loops interact (e.g., Olazabal et al., 2018; Singh and Chudasama, 2020). For example, in Martinez et al. (2018), climate change and water availability were identified as key drivers impacting the water-energy-food (WEF) nexus in Andalusia, Spain. Such findings may aid decision-making specific to the Andalusian agricultural community, but an overall understanding of *why* the WEF system was driven by specific variables is lacking. Causal logic, which elicits deep insights of system behavior according to how the reinforcing and balancing loops interact, would facilitate knowledge that is transferable to other locations. Instead, the complexities of feedback loops are often embedded within FCM-based simulations and are not used to inform the logic underlying the system (Harich, 2010). As such, FCM-based scenarios, when used in isolation, may be deemed black-box methods that obscure the non-linear developments emerging from within the model to influence dynamic behavior (Kaljonen et al., 2012).

As described by Richardson (2011), the foundations of systems-thinking extend far beyond stakeholder participation and derivation of system structures. When applied holistically, systems-thinking can be used to reveal how human actions impact the state of a system according to dynamic simulations and supporting causal logic. Dynamic, causal, and feedback-thinking elicits crucial information about the direction and central relationships of a system, which could reveal compensatory effects of human-environment behavior (Richardson, 2011). However, without an understanding of the strengths of the

system feedbacks (e.g., through FCM-based modeling), identifying such compensations may become elusive. For this reason, many studies reveal only a portion of the overall insights attainable from systems-based methods. In order to understand how specific interventions may shift the system trajectory toward or against policy goals, we must appreciate the full scope of systems-thinking as an integrated paradigm. While scenario-building may be used to specify high-leverage variables within the system, causal logic is necessary to reveal the source of system behavior. Particularly, when we aim to implement composite management strategies involving numerous altered variables, the system may diverge to produce unexpected outcomes resulting from complex interactions between opposing feedback loops.

Fuzzy logic employs the strengths of tacit stakeholder knowledge, which is knowledge embedded within stakeholder mental maps, but which may be difficult to explain comprehensively. By performing a mechanistic approach to elucidating system behavior, FCMs allow us to define the structure of the system using simple, pairwise relationships between two variables incrementally. Then, the 2nd-order effects of policy feedback processes may be simulated with the aid of computational software to identify when negative consequences of policy actions may be activated and/or to identify optimal combinations of synergistic policies (Capano and Howlett, 2019). As promoted by Richard Levins' theory of loop analysis, semi-qualitative modeling of signed diagraphs, alone, are insufficient for enhancing our understanding of policy strategies (Puccia and Levins, 1991). Instead, when feedback loops begin to interact beyond the initial order of behavior, the system may diverge into unexpected outcomes, which we must understand to reveal the underlying theory regarding system behavior in response to disparate policies. For

example, system stability resulting from an FCM-based scenario may reveal strong pathways for specific feedback loops in comparison to other loops. Opposing outcomes may result from a positive (i.e., reinforcing) feedback loop being embedded within the system that is not immediately obvious to the modeler. System behavior that alternates between outcomes could reveal a delayed positive feedback effect within the system. While CLDs inform a rich understanding of system interactions through qualitative storylines, and FCMs provide a mathematical basis for modeling such complex systems, scenario-based modeling alone "does not do justice to either the richness of the stories or the complexity of the models," (Kok, 2009). Therefore, this research promotes the integration of qualitative analysis (i.e., identifying and assessing feedback loops within a CLD) with semi-quantitative modeling (i.e., simulating system trajectory with FCM-based scenario building) to facilitate deep insight.

2.1.4 Toward Policy Coherence: Synergies & Trade-offs

Policy coherence is used to describe the extent to which a set of unique policies imposed on a system result in optimal (or sub-optimal) interactions between the system components toward achieving a common goal. While the literature is not consistent in defining policy coherence, this term is typically understood to define the areas of synergy and conflict between sets of policy choices within the system (Muscat et al., 2021; Reyes-Mendy et al., 2014). Policy conflict is used within the environmental literature to describe a phenomenon known as "policy resistance", where well-intentioned management strategies are hindered by unforeseen consequences evolving from systematic feedbacks (Sternam, 2002). Kotir (2020) describes policy resistance as "the tendency for an intervention to be jeopardized by the system's response to the intervention itself." Within the system dynamics literature, the primary means for circumventing policy resistance is

to transition the planning paradigm from a reductionist worldview toward a greater awareness of and appreciation for complexity. By approaching the problem as a dynamic structure of moving parts, each impacting one another through causality, an assessment of interacting feedbacks is assumed to reveal how the system would react if one of the components were altered by policy intervention (Roxas et al., 2019). However, as previously discussed, such assessments by visualization alone become impossible as the system grows larger. As noted by John Sterman, a leader in the field of SDM:

> *"Even if our cognitive maps of causal structure were perfect, learning, especially double-loop learning, would still be difficult. To use a mental model to design a new strategy or organization we must make inferences about the consequences of decision rules that have never been tried and for which we have no data. To do so requires intuitive solution of high-order nonlinear differential equations, a task far exceeding human cognitive capabilities in all but the simplest systems."* (Sternam, 2002).

Policy synergy is a term used to describe how well combined management strategies interact as a cohesive unit to accomplish more than the sum of separate policies. In other words, policies that exhibit synergy reinforce one another, according to the dynamic properties of the system feedbacks and their internal strengths, to manifest the policy objectives (Muscat et al., 2021; Nilsson et al., 2012). In adopting the view that policy coherence is an increase in synergies and a reduction in conflicts, it becomes clear that we should both identify the interacting feedback loops (e.g., causal mapping) and also identify which loops tend to drive the system response according to their inherent feedback strengths (i.e., FCM-based modeling). Failure to understand these processes often results in reductionist interventions aimed at "fixing" one facet of the problem, which may initiate non-optimal system behavior and defeat the original policy goal (Agyepong et al., 2012). To address such complex questions, this study stresses that the full scope of systems-thinking provides the optimal means for elucidating policy coherence by seizing and

integrating the strengths of distinct, but complementary, systems-based approaches. An example is presented in **Fig. 2** to demonstrate the concept of policy coherence as stemming from interacting feedback loops.

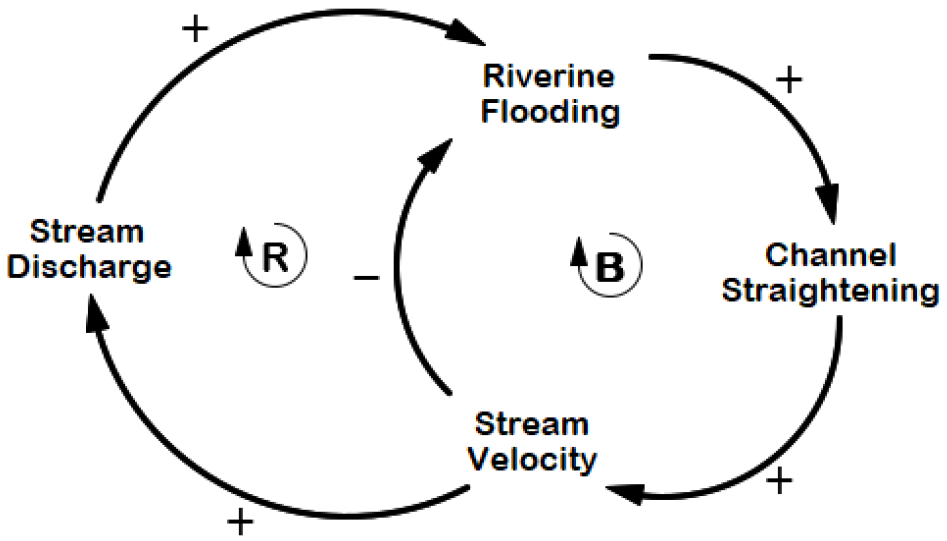

Fig. 2. Causal loop graphic depicting interacting feedback loops.

This graphic represents a common approach in floodplain management where natural streams are converted into concrete-lined channels to reduce riverine overflow by rapidly transitioning water further downstream. Here, a balancing loop is denoted with "B" to describe the tendency of channel straightening to reduce riverine flooding by increasing stream velocity. A synchronous reinforcing loop is denoted with "R" to highlight the amplifying effects of the channel intervention on stream discharge and, potentially, riverine flooding elsewhere within the system. Increased stream velocities at the project location may result in flooding elsewhere if the downstream discharge is not carefully balanced to accommodate additional inflow. Ideally, the reinforcing loop in **Fig. 2** would remain weaker than the balancing loop through careful engineering. However, this figure showcases how a policy change in one portion of the system could result in adverse impacts

elsewhere (e.g., amplified flooding downstream), thereby highlighting the need to understand the causal structure of the system *and* the strengths of the interacting loops.

2.2 Overlapping Co-benefits & Decision-making

NBSs have been shown to provide significant abatement of air and water pollutants, aid ecosystem connectivity, and preserve biodiversity through enhanced greenspaces in the urban environment (Anderson and Gough, 2020; García et al., 2020; Hansen et al., 2019; Song et al., 2019). Additional co-benefits have been widely demonstrated throughout the literature, including improvements in societal well-being, mental health, recreation, community, energy demand, urban heat, carbon sequestration, social capital, economic viability, crime, and noise pollution (Alves et al., 2019; Fenner, 2017; H. 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). **Table 1** summarizes the co-benefits associated with NBSs according to a recent, comprehensive literature review. According to Ruangpan et al. (2020), consideration of multiple co-benefits has been increasingly valued as a desirable goal throughout the NBS literature, yet the majority of planning studies have continued to prioritize stormwater abatement, due in part to a lack of comprehensive, geo-referenced datasets that are readily accessible. A right first step toward integrating coupled benefits within NBS planning is to represent various overlapping phenomena (societal, hydrological, environmental, and ecological) as explicit functions of space, encompassing the variety of scale and domains associated with holistic NBS systems.

Table 1. Summary of literature review of multifunctional NBS benefits.

	Challenge	Demonstrated NBS Co-benefit	Reference
Society	Morbidity	Improvements in various non-communicable diseases, including heart disease, diabetes, cancer, mental disorders, and chronic respiratory diseases.	(Mitchell and Popham, 2008)
	Social Vulnerability	Improved health and social outcomes, particularly in lower socio-economic populations.	(Luck et al., 2009)
	Economic Health	Improved land values. Increased tourism. Indirect economic benefits from improvements to local health.	(Vandermeulen et al., 2011)
	Mental Health	Improvements in mental stress, depression, general emotional well-being, sleep, anxiety, mood, aggression, and pain management.	(van den Berg et al., 2010)
	Physical Health	Improved levels of physical activity. Reduced obesity. Improved birth outcomes and pregnancy health.	(Kaczynski and Henderson, 2007)
	Crime	Reduction in crime rates, including improvements in incidences of theft and assault.	(Branas et al., 2011)
	Social Cohesion	Improved sense of community and pro-social behavior.	(de Vries et al., 2003)
Ecosystem	Diversity	Higher levels of biodiversity in various plant, insect, bird, mammal, and aquatic species.	(Tzoulas et al., 2007)
	Imperiled Species	Habitat preservation for native and non-native wildlife, including endangered and threatened species.	(Planchuelo et al., 2019)
	Habitat Connection	Increased movement of plants and animals between fragmented areas, resulting in improved conservation.	(Gilbert-Norton et al., 2010)
Environment	Air Pollution	Improved air quality, including abatement of particulate matter, carbon, ozone precursors, and indoor air.	(Nowak et al., 2006)
	Urban Heat Island	Evaporative outdoor cooling effects. Reduced indoor energy consumption and improved energy savings.	(Bowler et al., 2010)
	Noise Pollution	Improved levels of urban noise, including from air and traffic-related sources.	(Dzhambov and Dimitrova, 2014)
	Soil Erosion	Reduced risk of shallow landslides. Reduced soil erosion and enhanced catchment sedimentation.	(de Jesús Arce-Mojica et al., 2019)
	Water Quality	Removal of contaminants in greywater reuse. Improved water quality, including levels of nutrients, metals, suspended solids, oil/grease, oxygen, and chemicals.	(Boano et al., 2020)
Hydrology	Flooding	Improved peak runoff, delay, and attenuation. Reduction in total runoff volume. Reduced hydrological flashiness.	(Ruangpan et al., 2020)
	Coastal Protection	Coastal habitat protection. Mitigation for storms and sea-level rise.	(Ruckelshaus et al., 2016)
	Sewer Overflow	Reduced occurrence and magnitude of combined sewer overflows.	(Pennino et al., 2016)
	Drought	Agricultural protection. Improved irrigation, water availability and food security.	(Lottering et al., 2015)

2.2.1 Transdisciplinary Geospatial Data

Comprehensive data information systems for NBS functions have not been accumulated into a deployable format, particularly using the latest technological advances of web-based geospatial information systems (GIS). To amalgamate GIS services toward enhanced NBS decision-making, we necessitate multidisciplinary datasets that are geospatially robust, user-friendly, and curated for specific properties of societal and environmental importance. Within the NBS literature, some studies have linked stakeholder interaction with web-apps for enhanced decision-making (Meerow, 2019). However, in such applications, the users are still required to supply the local data layers and are limited in which types of information the tools will accept (i.e., it is not possible to search various data layers and then decide which criteria are most important). Other applications have compiled various datasets pertinent to NBS planning into a web-based platform (GLA, 2018) but are location-specific and are generally presented at a coarse scale. Many of the latest NBS web applications described by Ruangpan et al. (2020) tend to be information portals designed to inform the user of generalized co-benefits through textual descriptions and do not contain spatial evidence for local siting. The UN IPCC panel noted a considerable research gap regarding holistic data frameworks for NBS spatial trade-offs, including a substantial lack of integrated social reference data, thereby urging rapid development toward novel data streams that could facilitate transdisciplinary NBS research (Frantzeskaki et al., 2019). By harnessing the power of web-based GIS, a measurable data framework is achievable to better understand how NBSs impact the surrounding environment while also investigating how local characteristics, in turn, impact the efficacy and co-benefits of NBSs.

2.2.2 Web-based Geospatial Information Systems

Web-based GIS is defined here as a GIS system that utilizes cloud technologies to communicate data, functionality, and user-interface through online mapping. Web-based GIS applications have increased significantly in recent years due to improvements in cloud computing and storage (Veenendaal et al., 2017). As high-resolution datasets for Earth-system sciences have proliferated with advances in remote sensing technologies, web-based GIS tools for environmental applications have become more common (Guo et al., 2017). Many remote sensing datasets used in hydrological modeling represent multiple decades of observations and are approaching, or exceeding, the petabyte-scale in data volume (1 petabyte (PB) = 1,000,000 gigabytes (GB)) (McCabe et al., 2017). For example, the uncompressed size of the global terrain dataset geo-referenced in NBS-Geo, alone, is over 90 petabytes (Esri, 2021a). As such, large-volume geospatial datasets for environmental applications are becoming increasingly difficult to manage on local computers and servers. To meet this challenge, web-based GIS data tools have been proposed to better assess issues of societal and environmental importance through geospatial visualization (Iadanza et al., 2021; Kitsiou et al., 2021; Mhangara et al., 2019; Tian and Huang, 2019; Vacca et al., 2018).

Web-based GIS platforms have been applied to hydro-environmental studies since the early 2000s (Sugumaran and DeGroote, 2010) through decision-support systems for water resources management (Engel et al., 2003) and environmental planning (Granell et al., 2010; Sugumaran et al., 2004). Data discovery, visualization, processing, and analysis techniques have been improved through web-based GIS for various topics such as hydrology (i.e., HydroDesktop (Ames et al., 2012)), ecology (Boyd and Foody, 2011; Flemons et al., 2007), earth-observations (i.e., JEODPP (Soille et al., 2018), Google Earth

Engine (Gorelick et al., 2017)), and site-specific issues of integrated phenomena (Khalil et al., 2014; Lehmann et al., 2017; Mekonnen and Gorsevski, 2015). While such data platforms have successfully linked users with vast amounts of spatial information, the results continue to be in the format of search-and-discovery, with the user needing an idea of what types of data to investigate for their specific end-goals. These GIS services have also been typically constrained to a singular domain and/or study area with limited inclusion of sociological information.

To accommodate transdisciplinary data analysis, spatial mashups have become common components of web-based GIS where numerous geospatial layers are overlaid within one user interface for easy access and rapid assessment of multiple sets of information (Zhou et al., 2014). Such web-based data mashups are becoming increasingly popular in environmental applications (Feng et al., 2020; Granell et al., 2016; Sun et al., 2019; Zhang et al., 2019). Spatial mashups were spawned after the advent of Asynchronous JavaScript and XML (AJAX) technologies, which are used to send and receive datasets from a remote server without disrupting user interactions. The success of AJAX led to the development of various Application Programming Interfaces (APIs), which allowed combination of remotely sensed and user-defined local data to create curated mashups. APIs provide software-to-software capabilities, beyond the traditional user-to-software interactions, thereby facilitating combination of different web services and rapid retrieval and linkage of numerous online repositories simultaneously (Veenendaal et al., 2017). Esri's Living Atlas, which is a core component of the approach described in **Section 3.2**, is an example of a widespread geospatial mashup that leverages API technologies to connect users with data and additional interactive capabilities, including widgets and

spatial tools, to foster communication and collaboration across disciplines. In the Living Atlas, numerous maps and map servers are packaged through a standardized interface known as the Representational State Transfer (REST) API. This service-based architecture allows for a bridging of the knowledge gap between data and end-users, thereby facilitating engagement of multiple disciplines across varying scales (Veenendaal et al., 2017).

2.2.3 Hierarchy of Data-Wisdom Relationships

Comprehensive data systems, alone, will not translate into actionable decisions and useful insights without human interaction. The DIKIW pyramid (Data, Information, Knowledge, Intelligence, Wisdom) is a popular construct within data systems science to represent the hierarchy of relationships between foundational datasets and user-derived wisdom (Veenendaal et al., 2017). Data, which are recorded readings represented by symbols, function as the basis for wisdom. Data, however, is meaningless without context or systematic organization, which when incorporated, becomes information. Information then transforms into knowledge upon integration of human expertise. Intelligence develops when human agents are able to consider multiple rationales (i.e., uncertain futures) about the environment through the use of organized datasets. Wisdom, then, evolves from the incorporation of human capacitance to withstand or transform decisions regarding future scenarios through experiential learning (Liew, 2013).

The DIKIW classification scheme, depicted in **Fig. 3** (adapted loosely from Veenendaal et al. (2017)), is a visualization of how robust GIS web applications contribute to deeper systemic insights regarding overlapping phenomena. Web applications transcend beyond standard GIS portals, which contain vast amounts of ‘big data’, toward curated subsets of multidisciplinary information to begin discovering spatial patterns through the lens of the observer. As patterns become elucidated, the user is then able to consider multiple future

scenarios, thereby fostering intelligence toward actionable decisions. As such, this research emphasizes not only the GIS technologies underlying a novel NBS data system but also the usability of such a platform and the insights that may be garnered through added-value interactive capabilities (e.g., **Sections 3.2.4, 4.2.2**).

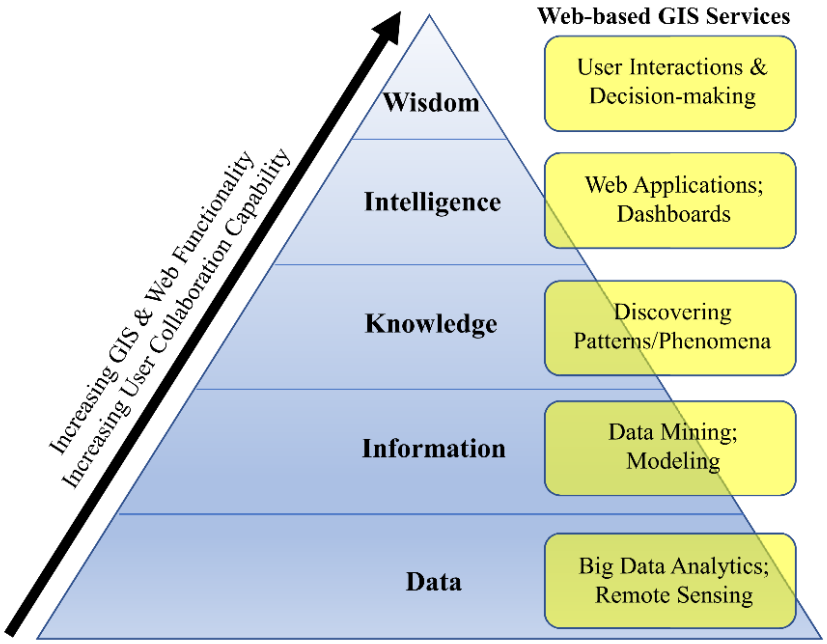

Fig. 3. Hierarchy of data-wisdom interrelationships.

2.3 Spatial Allocation Optimization

2.3.1 NBS Optimization Tools

Optimization tools are used in sustainability modeling to determine the priority locations of desired benefits. Systems-based optimization modeling for water resources was first pioneered by the Harvard Water Program (1955-1960), where multi-objective optimization methods were proposed for enhancing economic development and planning of large-scale water infrastructure in the post-war construction era (Sivapalan and Blöschl, 2017). As NBSs became increasingly popular, various spatial planning tools have been proposed for enhanced implementation. Spatial optimization tools are used to analyze co-evolving factors that have been shown to result in conflicting NBS responses depending

on local conditions (i.e., spatial aggregation, impervious coverage, contributing drainage area, slope of terrain, distance to receiving stream) (Zhang and Chui, 2018). In other words, the ideal arrangement of NBSs is debatable, and we require modeling tools to investigate the optimal spatial allocation in a location-dependent manner (Kabisch et al., 2016; Sarabi et al., 2019; Zhang and Chui, 2018). According to Zhang and Chui (2018), the following hierarchy of tool typologies have been commonly used to evaluate the optimal spatial placement of NBS systems, with specific examples shown in **Fig. 4**:

1) Screening Tool (ST) – Identifies general locations of NBSs at the regional scale by overlaying geospatial datasets with historical areas of flooding.
2) Spatial Allocation Optimization Tool (SAOT) – Combines topography with hydrological modeling to simulate optimized locations according to the local hydrograph response.
3) Planning Support System (PSS) – Enhances STs with data visualization and weighting criteria for stakeholder interaction.

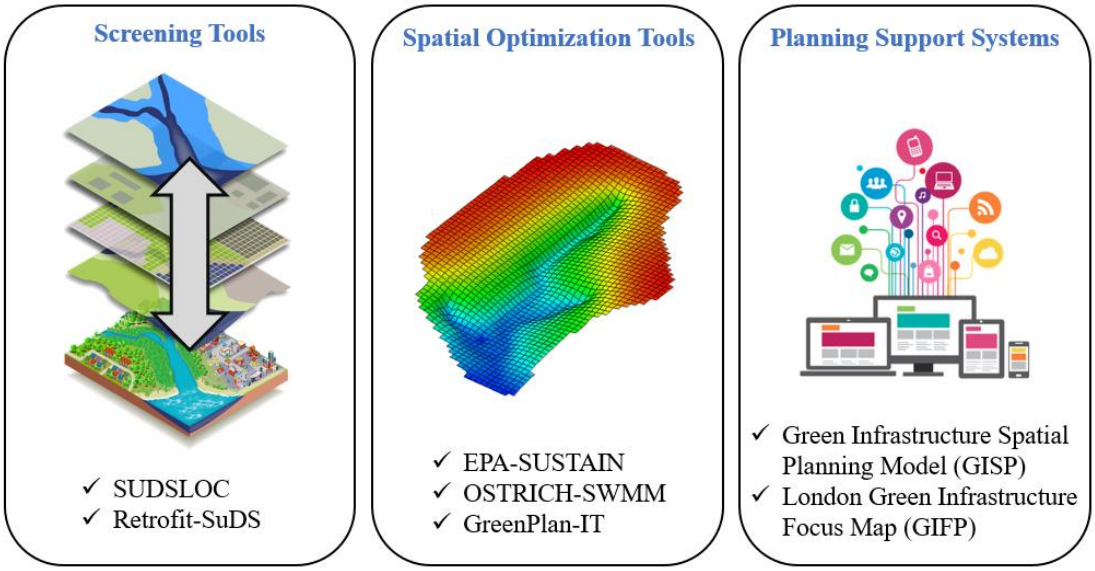

Fig. 4. Typologies of common nature-based solution planning tools.

2.3.1.1 Screening Tools

STs are preliminary tools used to define a general planning area from coarse datasets, and as such, are not highly accurate. Most of these tools use GIS for prioritization and may

integrate spatial distribution of co-benefits at this stage, although many do not. STs are also used to determine the general selection of NBS types from various options (i.e., green roofs, bioswales, permeable pavement, detention ponds). Such preliminary assessments are often used to narrow the planning focus for further detailed modeling and optimization (Zhang and Chui, 2018). SUDSLOC is a popular GIS-based decision support tool that combines watershed modeling with biophysical and socio-economic suitability criteria. Retrofit-SuDS is another NBS ST that informs the user of general site suitability locations using a decision tree matrix (Kuller et al., 2017).

2.3.1.2 Spatial Allocation Optimization Tools

Spatial allocation optimization tools (SAOTs) integrate physically-based models with high-resolution topography and optimization techniques, but these complex tools lack inclusion of social co-benefits and participatory planning. Advanced SAOTs apply optimization algorithms to generate sample populations of placement scenarios. The most common optimization techniques used in NBS SAOTs are classic optimization (linear programming, dynamic programming), evolutionary algorithms, and particle swarm optimization (Duan et al., 2016; Limbrunner et al., 2013; Reed et al., 2013; Zhang and Chui, 2018). NBS SAOTs are typically coupled with two-dimensional hydrological and hydraulic modeling software, which contain limitations in the scale of analysis due to lengthy data and computational requirements (Macro et al., 2019; Ruangpan et al., 2020). The most popular two-dimensional modeling programs used for NBS analysis are SWMM and SUSTAIN, where numerous studies have been conducted to analyze hydrograph characteristics for sub-watershed NBS implementation with varying results regarding optimal siting (Huang et al., 2019; Jarden et al., 2016; Jato-Espino et al., 2016; Radinja et al., 2019; Zellner et al., 2016). Both SWMM and SUSTAIN are considered process-based

approaches where simulations are conducted only for small-scale processes (i.e., infiltration, evapotranspiration, conveyance routing) due to the significant amounts of data and computational processing required.

Several SAOTs have been developed that couple optimization techniques with high-resolution models. A popular SAOT tool for coupling NBS optimization with SWMM modeling is the EPA-SUSTAIN program, which models urban stormwater and optimizes spatial placement as a function of cost (Lee et al., 2012). OSTRICH-SWMM was designed to incorporate multi-objective optimization into SWMM modeling for low impact development (LID) systems (Macro et al., 2019). GreenPlan-IT is another popular SAOT that was built upon the SWMM model for optimizing NBS drainage system allocation. Many additional studies have coupled the popular Nondominated Sorting Genetic Algorithm II (NSGA-II) with modeling to identify optimal NBS locations and analyze tradeoffs between hydrological efficiency and cost (Alamdari and Sample, 2019; Giacomoni and Joseph, 2017; Krebs et al., 2013; Mani et al., 2019; Muleta and Boulos, 2007; Oraei Zare et al., 2012; Raei et al., 2019; Tao et al., 2014; Zhang et al., 2013).

An alternative to the process-based, small-scale model optimization is the practice-based approach where hydrological effects are aggregated into one parameter value, typically the curve number (CN) (Ahiablame et al., 2012). A popular practice-based tool in NBS optimization is L-THIA-LID, which is used to simplify hydrological processes for widespread planning (Liu et al., 2017, 2016b, 2016a). Liu et al. (2016b) presented a multi-objective optimization tool that is coupled with L-THIA-LID through a lookup table. This tool incorporated the efficiency of a parallel computing framework and a multi-level/multi-algorithm spatial optimization to investigate optimal NBS placement configurations in

terms of hydrologic efficiency with the CN methodology (Liu et al., 2016b, 2016a). StormWISE is another optimization framework for NBS planning that couples L-THIA-LID and the CN methodology (McGarity, 2012). While these decision-support tools combine hydrological modeling with NBS optimization at the watershed scale, they lack stakeholder interaction and are limited to efficacy in terms of water balance without considering additional social factors or co-benefits.

2.3.1.3 Planning Support Systems

PSSs combine selection and evaluation processes into an integrated decision support system for enhanced stakeholder involvement. Two popular examples of nature-based PSSs are the Green Infrastructure Spatial Planning Model (GISP) (Meerow and Newell, 2017) and the London Green Infrastructure Focus Map (GIFP) (GLA, 2018). These tools provide stakeholder options for assigning weights that prioritize preferred NBS benefits (i.e., flood risk, water quality, air quality, social vulnerability, green space, and heat island) according to the value of each identified variable. Hydro-environmental factors are incorporated as pre-defined maps of areas that typically flood (i.e., 1% annual inundation boundary) which are superimposed in GIS and are not further evaluated through modeling or optimization algorithms. The most common approach used in PSSs involves multi-criteria decision analysis (MCDA), which assigns stakeholder weights to geospatial datasets to derive hotspots for optimal planning (Alves et al., 2018; Loc et al., 2017). Such PSSs integrate data with stakeholder preferences for identifying general tradeoffs, hotspots, and synergies between stormwater abatement and other co-benefits. They rely on geospatial data compilation to define risks and benefits without considering the complex processes that underlie NBS performance as spatial configurations are altered. Typically, PSSs are simplified GIS representations of various options and neglect to capture the

dynamics of NBS processes through hydro-environmental modeling (Kuller et al., 2017; Scholz, 2006).

2.3.2 Integrated Optimization Frameworks

There exists a large knowledge gap regarding how to investigate NBSs on a large-scale while incorporating societal characteristics. PSSs are a right first step in this direction, however, PSSs do not typically include water balance modeling. Multi-objective optimization tools capture watershed processes while lacking stakeholder participation. As described, NBS multifunctionalities are often implied within the literature but are rarely accounted for explicitly within spatial optimization tools, where stormwater volume reduction remains the primary driver for NBS allocation (Madureira and Andresen, 2014). Social phenomena are not typically captured within SAOTs in a manner that also considers dynamic hydro-environmental changes. For this reason, studies are beginning to approach NBS optimization comprehensively, where environmental, social, economic, and stormwater conditions are integrated into one framework (Frini and Ben Amor, 2019; Kuller et al., 2017; J. Li et al., 2017). For example, (Kaykhosravi et al., 2019) presented a framework for optimizing NBS decision-making by using publicly-available geospatial datasets and GIS-MCDA to derive spatial indices for hydrologic, socioeconomic, and environmental demands. However, we necessitate further research in this direction.

The lack of integrated ST+SAOT+PSS tools to capture NBS multifunctionalities while exchanging information between modelers and stakeholders has been noted within the literature (Kabisch et al., 2016; Ruangpan et al., 2020; Zhang and Chui, 2018). Robust decision-support tools are needed in the early stages of NBS planning that integrate sustainability, multifunctionality, urban ecology, socio-economics, and resilience thinking in a manner that engages key decision-makers for cohesive action toward preferred

solutions (Lovell et al., 2014). As such, there exists an opportunity to optimize NBS planning by integrating watershed processes, social co-benefits, and stakeholder participation into a unified framework. Instead of relying on highly-complex modeling, or overly-simplified priority weightings, this study suggests a middle-ground for NBS frameworks that can be applied at cascading scales.

3. METHODOLOGY

3.1 Holistic Systems-thinking for Policy Coherence

To explore the feedback effects of system dynamics on NBS policies, a half-day virtual workshop was conducted with stakeholders from the greater-Houston metropolitan region. A GMB session was executed to elucidate prominent relationships between NBS adoption and various social and institutional constructs. A semi-structured scripting protocol was used to guide the stakeholders in deriving a shared CLD and identifying the strengths of internal relationships. The causal system was then transposed into a weighted FCM, which was used to simulate various "what-if" management approaches. For each simulation, a unique policy (or set of policies) was propagated throughout the system to identify relative change of NBS implementation. The collective strategies were compared and ranked to elucidate areas of policy synergy and conflict. Finally, the balancing and reinforcing properties of the CLD feedback loops were used to confirm and better understand the policy implications resulting from the FCM-based scenarios.

3.1.1 Stakeholder Workshop

The virtual stakeholder workshop was held on July 9, 2021 to capture the mental models of experts who had recently been involved with NBS implementation efforts in Houston, Texas, USA. The workshop included nine participants across three jurisdictional scales (i.e., local, municipal, and regional-level). Each of the stakeholders were well-known within the community as having a historical involvement in NBS adoption and/or policy design. Several of the participants were previously involved in developing guidelines associated with NBS initiatives and frameworks. For example, NBS adoption was encouraged through the "Incentives for Green Development" program, which

supported green development with project awards, tax abatements, and expedited permits (Bloom et al., 2019). The "Resilient Houston" strategy also promoted sustainable infrastructure by identifying goals for green development and by highlighting the role of NBSs in climate mitigation, social equity, and water management (Aho and Sarkozy-Banoczy, 2020). A community-driven "Houston Climate Action Plan" provided evidence-based strategies to achieve carbon neutrality, which included enhanced levels of green space (City of Houston, 2020). Regional partners encouraged nature-based development through numerous design standards, planning guidelines, and pilot projects (HCFCD, 2020; RGME, 2021; Storey et al., 2011). Moreover, several taskforces were deployed to integrate community members with city and county officials for NBS development. **Table 2** summarizes the various institutions, roles, and NBS backgrounds represented in the GMB workshop. The workshop was facilitated by leading the participants through a series of GMB scripts from the open forum "Scriptapedia" (detailed in **Appendix A**), which have been verified by the SDM community and are considered best-practices for CLD group modeling. The following scripts were used for the NBS case study:

1) Logistics and Room Set-up: Used to format the virtual environment by identifying necessary tools and exploring options within the workshop platform.

2) Chicken and Eggs Example: Used to introduce the concept of a dynamic systems and causal loop models by depicting a story of chickens who needed to cross a busy road due to over-population. Feedbacks included birth, death, and management interventions to aid the chicken population (e.g., installing traffic barriers, building a fence, removing chickens).

3) Variable Elicitation: Used to facilitate a group discussion and identify causal variables to describe social and institutional feedbacks associated with nature-based solutions (including both barriers to and responses from successful implementation of nature-based solutions).

4) Causal Mapping with Seed Structure: Used to quickly illustrate a system of interacting feedbacks using seed variables from Script 3, demonstrating concepts of causation, polarity, balancing and reinforcing loops, and dynamic change.

5) Creating Causal Loop Diagram from Variable List: Used to translate the identified variables into causal relationships and to define the strength of each feedback.

6) Model Review: Used to elicit the balancing and reinforcing loops within the system and to guide reflection of the major feedbacks where model-based insights emerge from the interaction of multiple feedback loops.

The stakeholders were guided through each of the above scripts in successive order. Hypothesized variables were identified on a virtual whiteboard through a collective group discussion. The facilitator then drew the causal relationships, as defined by the stakeholders, within a web-based platform for real-time visualization and optimization. After the workshop, the causal loop sketch was converted into a CLD using *Vensim* software and then emailed to the stakeholders for validation. A verbal transcript of the recorded session was reviewed during the translation process to ensure variables and causal relationships were correctly identified and to highlight any areas of ambiguity. Prior to the workshop, the author identified key socio-institutional variables impacting NBS implementation per a recent literature review and grouped the factors within four primary themes to differentiate the dynamic components of the system (e.g., community buy-in, social culture, institutional characteristics, and engineering and maintenance). These themes where then further categorized into socio-institutional barriers, management opportunities, and exogenous factors for the workshop. During the preparation phase (Script 1), a virtual whiteboard was drafted with themed boxes, each color-coded for coherency of variable-types throughout the GMB process. One seed variable was inserted within each box as a preliminary example. During the workshop, the stakeholders were introduced to a CLD example (Script 2), which provided a foundation for the types of variables to be considered in systems modeling. The stakeholders were then shown the virtual whiteboard and asked to consider how unique factors have limited or advanced NBS

efforts according to their local experiences. Through a group discussion, participants described numerous causal factors associated with NBS implementation (Script 3). The variables were documented by the facilitator in real-time and grouped according to theme. The live whiteboard sessions for variable elicitation are depicted in **Fig. 5**.

Table 2. Stakeholder roles and experience for NBS group workshop.

Scale	Role	NBS Experience
Local	Community Engagement	Environmental coalitions and local communication of grassroots efforts. ✓ Houston Climate Action Plan ✓ Resilient Houston Strategy
Local	Ecology	Conservation leadership of local ecological restoration.
Local	Civil Engineering	Engineering for design and construction of numerous NBS projects throughout greater-Houston region.
Local	Environmental Engineering	Sustainability consulting expert and engineer for numerous NBS projects, involving a variety of community builders. ✓ Harris County Residential Green Infrastructure Standards ✓ Houston Incentives for Green Development ✓ Harris County Community Flood Resilience Task Force ✓ Member, Houston Drainage Task Force
City	Public Works Planning	Rehabilitation, construction, and planning of water resources and environmental projects. ✓ Resilient Houston Strategy
City	Infrastructure Maintenance	Maintenance of public works facilities, including green development.
City	Sustainability & Recovery	Transdisciplinary resilience-building efforts for region, including natural disasters, infrastructure, and social inequality. ✓ Houston Climate Action Plan ✓ Resilient Houston Strategy ✓ Incentives for Green Development
Region	Stormwater Planning	Regional drainage planning for county, including stormwater conveyance and quality for NBS. ✓ Harris County Low Impact Development Infrastructure Design Criteria ✓ County engineering and planning for regional low-impact development and green infrastructure.
Region	Public Works Planning	✓ Harris County Low Impact Development Infrastructure Design Criteria ✓ Houston Drainage Task Force

Table 3. Literature review of key socio-institutional barriers to NBS adoption.

	Variable	References	Key Considerations
Community Buy-in	Economic Incentives	(Baptiste et al., 2015; Tayouga and Gagné, 2016; Vogel et al., 2015)	Subsidies, grants, loans, fee reductions. Incorporated into local development plants. Drainage tax/fee reduction for individual residents.
	Educational Opportunities	(Chaffin et al., 2016; Derkzen et al., 2017; Thorne et al., 2018)	Community perceptions and understanding of NBS functionality and benefits. Outreach programs. Media reporting.
	Public Participation	(Bissonnette et al., 2018; Cohen-Shacham et al., 2019)	Adaptive governance structure. Targeted and strategic citizen involvement in selection and planning process. Neighborhood workshops.
Social Culture	Cultural Values	(Derkzen et al., 2017; Solheim et al., 2021; Thorne et al., 2018)	Traditional versus progressive engineering culture. Public perception shift. Fear of perceived risk to change. Lack of sense of urgency.
	Resilience Strategies	(Derkzen et al., 2017; Zuniga-Teran et al., 2020)	Capacitance building in vulnerable and marginalized communities.
	Co-benefits	(O'Donnell et al., 2017; Ramírez-Agudelo et al., 2020)	Identification of co-benefits to support shared set of values and community support
Institutional Characteristics	Fragmentation	(Chaffin et al., 2016; Ellis and Lundy, 2016; Kabisch et al., 2016; Ramírez-Agudelo et al., 2020; Solheim et al., 2021; Vásquez et al., 2016; Wamsler et al., 2020)	Central, singular NBS department. Integrated across sectors, separate from other utilities. Transverses multiple jurisdictions. Interagency work. Active cohesion.
	Financing	(H. Li et al., 2017; McRae, 2016; O'Donnell et al., 2017; Solheim et al., 2021; Thorne et al., 2018; Zuniga-Teran et al., 2020)	Understanding cost comparison to grey-infrastructure. Quantification of co-benefits. Combined funding sources. Adequate economic resources. Competing priorities.
	Regulatory Frameworks	(Dhakal and Chevalier, 2016; Gersonius et al., 2016; Levy et al., 2014; O'Donnell et al., 2017; Sarabi et al., 2020; Solheim et al., 2021)	Less stringent than grey-water, improves costs and implementation. Defined legal standards. Thresholds to trigger NBS stormwater management. Confusion/conflicting provisions. Regulations regarding long-term maintenance requirements.
Engineering & Maintenance	Design Standards	(Kronenberg, 2015; Solheim et al., 2021; Zuniga-Teran et al., 2020)	Uncertainties regarding how NBSs work locally. Technical manuals. Spatial planning guidelines.
	Technical Experience	(H. Li et al., 2017; O'Donnell et al., 2017; Solheim et al., 2021; Wamsler et al., 2020; Zuniga-Teran et al., 2020)	History of past project success. Certified expertise. Workshops and trainings. Staff turnover of NBS expertise.
	Maintenance	(Kabisch et al., 2016; H. Li et al., 2017; Ramírez-Agudelo et al., 2020; Thorne et al., 2018)	Regular inspections, monitoring guidelines. Cost of regular maintenance versus low-maintenance design options.
	Pilot Projects	(H. Li et al., 2017; Li et al., 2018; Zuniga-Teran et al., 2020)	Political leadership and champions. Successful community pilot projects (e.g., tours, educational signage, press coverage).

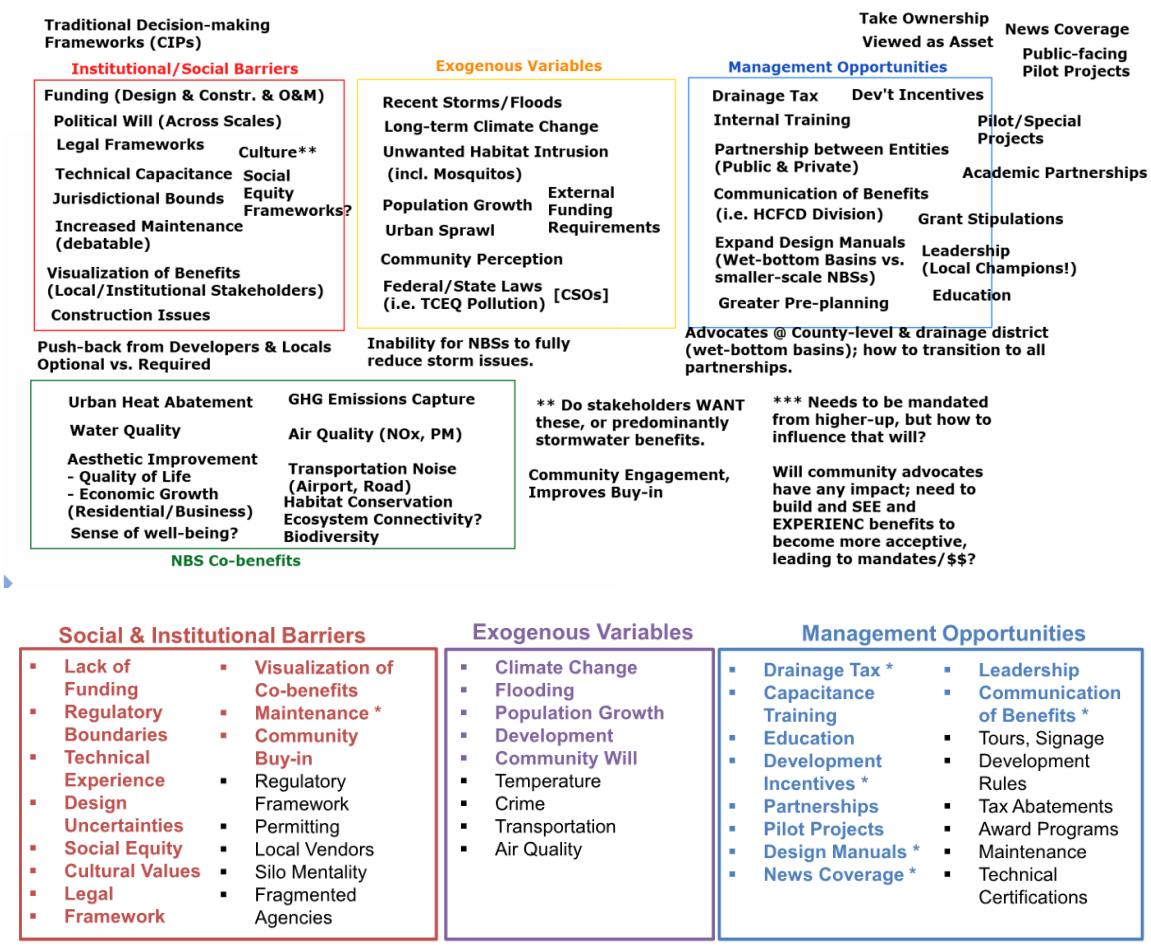

Fig. 5. (top) raw variable elicitation, (bottom) amalgamated variable elicitation.

3.1.2 Causal Loop Logic

The facilitator then selected several variables from the elicitation exercise and drew them as nodes within a live web-based platform called *Loopy* (ncase.me/loopy). Causal relationships and feedback loops were described and demonstrated visually within the shared web interface (Script 4). The participants were then asked to describe their understanding of dynamic behavior between the different elements (Script 5). During the live modeling session, CLD connections were drawn as one-way arrows between variables using the following polarity notations: positive (+), such that related variables changed in the same direction, or negative (-), where a change in one variable had an opposing impact

on the linked variable. The stakeholders discussed causal relationships between the identified variables, which led to group agreement or uncertainty, often stimulating deeper considerations of the underlying dynamics. As the stakeholders communicated, the facilitator moved variable nodes within the *Loopy* platform and marked the causal links to correspond with the group understandings. The stakeholders were also asked to define, qualitatively, the strength of connections between each variable, which were recorded by the facilitator. Feedbacks that were deemed to be particularly strong were denoted with three causal arrows in *Loopy*, and moderate connections were identified with two overlapping arrows. All other causal relationships were depicted with a single arrow. For purposes of simplicity, this GMB exercise did not consider time delays, as the resulting CLD was not intended for predictive modeling. This approach was meant to mimic the use of color-coded sticky notes often used in GMB (Andersen and Richardson, 1997; Inam et al., 2015), thereby facilitating a virtual workshop environment with interactive group discussions and real-time causal loop diagramming. The causal loop sketches derived from the live workshop are depicted in **Fig. 6**.

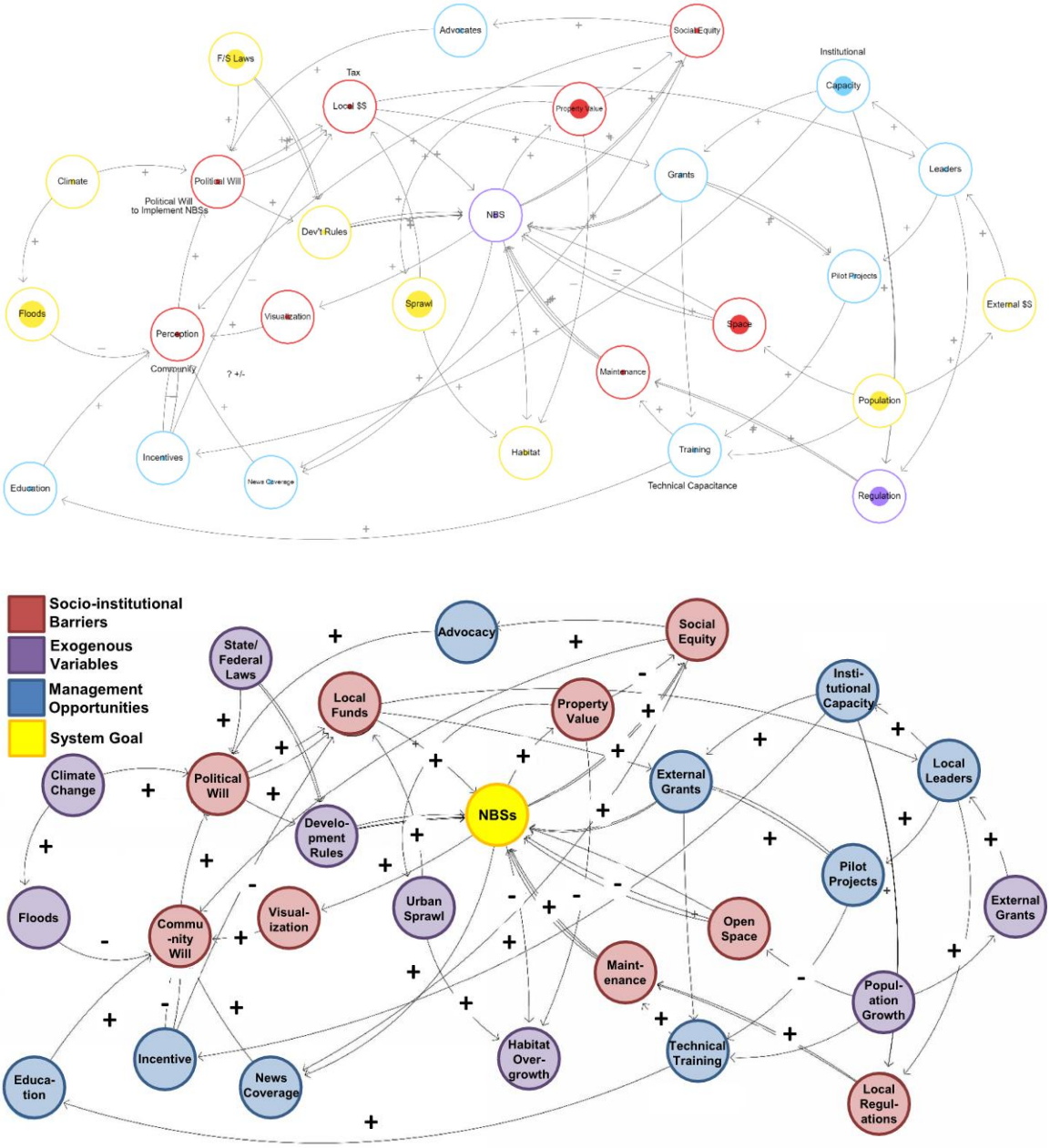

Fig. 6. (top) raw causal loop sketch (*Loopy*), (bottom) optimized CLD (*Vensim*).

The facilitator then translated the causal loop sketch into a CLD using the *Vensim* software, which is a widely-used system dynamics platform (Eberlein and Peterson, 1992). During the translation process, causal connections were compared to the recorded workshop transcript and optimized, where necessary, for coherency and accurate representation of the stakeholder discussions. For example, floods and climate change were deemed redundant variables (as they both provide a similar exogenous impact in the system) and were therefore merged by the modeler. The optimized CLD was emailed to all stakeholders for final validation, and no discrepancies were noted.

3.1.3 Fuzzy Mapping

The preceding steps identified the stakeholders' understanding of key system variables and how they interact amongst one another to facilitate, or hinder, local NBS implementation. These system components provided the qualitative foundation for explaining causal relationships. Next, the CLD was transposed into a semi-quantitative FCM model using the web-based mapping suite *Mental Modeler* (Gray et al., 2013), a necessary step to structure the system for dynamic scenario-building of decision-making strategies (Gray et al., 2015). The CLD variables and causal connections were depicted graphically within *Mental Modeler* (**Fig. 7**). To prepare the map for scenario development, the causal variables needed to be further categorized according to: 1) Those variables which the stakeholders have agency to change (i.e., management opportunities), and 2) Those variables that impacted the system but which this specific cohort of stakeholders did not possess decision-making power to change (i.e., exogenous factors).

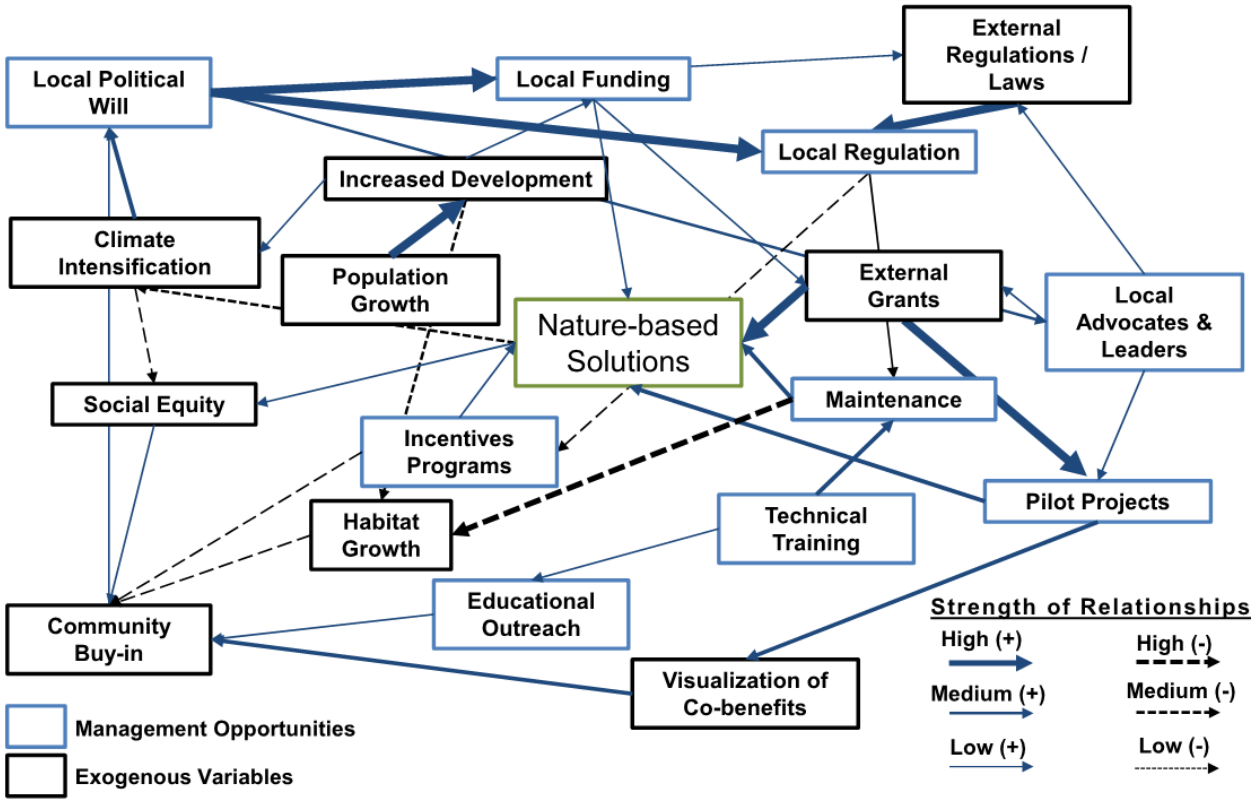

Fig. 7. Key socio-institutional challenges and their connections.

The degree of influence for each causal link was then defined with fuzzy logic according to the stakeholder perceptions during the GMB session. A weight of -1 to +1 was used to identify the strengths of system feedbacks according to the following categories and respective scores: low strength (±0.25), medium strength (±0.50), high strength (±0.75), where '+' represented positive causality, and '-' described negative causality. A score of 1 was reserved for "clamping" key decision variables for scenario development, described further in **Sect. 3.1.3**. Because FCMs are derived from graph theory, the system structure may also be represented mathematically by a square adjacency matrix (i x j variables). The NBS cognitive map was translated into an adjacency matrix, as shown in **Table 4**, which summarized the strengths of connection between all of the FCM variables.

Table 4. Adjacency matrix for fuzzy cognitive map.

	Development	Laws	Population	Climate	NBSs	Outreach	Training	Pilots	Grants	Incentives	Advocates	Habitat	Buy-in	Equity	Politics	Co-benefits	Maintenance	Funding	Regulation
Development				¼								-½						¼	
Laws																			¾
Population	¾																		
Climate														-¼	½				
NBSs				-½										¼					
Outreach													¼						
Training						¼											½		
Pilots					½		¼									½			
Grants					¾			¾											
Incentives					¼								-¼						
Advocates		¼						¼	¼										
Habitat													-¼						
Buy-in															½				
Equity			-¼																
Politics		¼																¾	¾
Co-benefits													½						
Maintenance					½							-¾							
Funding					½				¼										
Regulation										-¼							½		

3.1.4 Simulating Management Strategies

The management opportunities were incorporated into "what-if" scenarios to better understand how a change in local policy would impact the resulting state of the NBS variable. FCM-based scenarios are used to alter specific variables and trace causal propagation throughout the system. FCM simulations use the adjacency matrix to represent the strengths of interconnections and end-state vectors to characterize the degree of variable change once a scenario is activated. Here, the degree of activation for each variable within the proposed management strategy was assigned a value of +1.00, also known as "clamping" within the FCM literature (Gray et al., 2015), and the feedback effects on the NBS state vector were noted. FCM-based scenarios quantify dynamic interactions between

system components for discrete time-steps until the system converges to equilibrium by applying formalized activation rules and transformation functions to the adjacency matrix. This study used the Kosko's activation rule, **Eq. (1)**, and the hyperbolic-tangent transformation function, **Eq. (2)**, in *Mental Modeler*, which are detailed by Gray et al. (2013, 2015). The activation rule is given by

$$A_i^{(t+1)} = f\left(\sum_{j=1}^{n} w_{ji} A_j^{(t)}\right), \tag{1}$$

where, $A_i^{(t+1)}$ is the value of variable V_i at time step $t+1$, w_{ji} is the weight of connection between variable V_i and V_j, n describes the total number of variables in the system, $A_j^{(t)}$ represents the numerical value of variable V_j at time step t, and f is the transformation function (e.g., sigmoid function, hyperbolic tangent function, step function).

The hyperbolic-tangent function was chosen since values were allowed to become negative throughout the simulation (meaning, a negative policy could become less efficient after the simulation than had no policy been implemented) (Kokkinos et al., 2020). The hyperbolic-tangent transformation equation for any function $f(x)$ is described by

$$f(x) = \frac{e^{2x} - 1}{e^{2x} + 1}. \tag{2}$$

The final FCM contained 9 management opportunities out of the 19 total system variables. From these variables, 129 fuzzy scenarios were identified by assuming the stakeholders would implement either a single policy (n=9), a combined set of two policies (n=36), or a combined set of three policies (n=84), further described in **Sect. 3.1.5**. An example of the outputs from FCM-based scenario-building is demonstrated in **Fig. 8**, where unique variables are clamped to assess dynamic system change in the remaining state

variables. Here, the policy variable(s) listed in each chart title are clamped to a value of +1.00, and the system is activated according to Kosko's activation rule and the hyperbolic transformation function. The system stabilizes after a number of time-steps, and the changes in each variable state vector between the status quo and the final dynamic simulation are graphed as a relative percentage. NBSs, which are the goal variable for this system, are shown in green within **Fig. 8**.

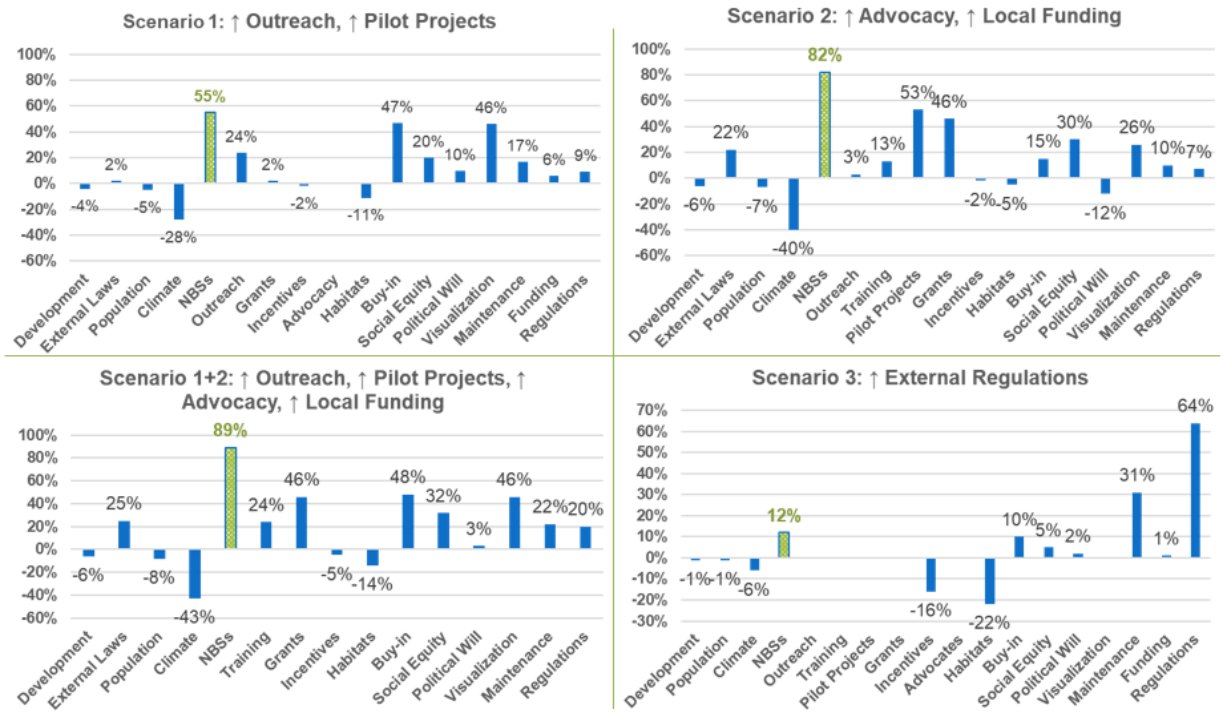

Fig. 8. Scenario output from FCM-based modeling.

3.1.5 Identifying Policy Synergies and Conflicts

Policy analysis describes the sensitivity of the model to the policies, or rules of human control, regarding the overall system behavior. By altering one of the model variables and assessing the resulting system outcome, patterns begin to emerge that reveal which policies would lead to optimal results or policy resistance (Barlas, 2002). Here, the single-policy strategies were compared with the multiple-policy strategies to identify areas of synergy

(i.e., combined policies produce a more favorable state change than policies implemented in silo) or conflict (i.e., interacting policies produce a lesser state change than had each policy been implemented separately) embedded within the dynamic behavior of the system (Stepp et al., 2009). These concepts are represented by **Eq. (3)** and **Eq. (4)**, respectively:

<u>Policy Synergy</u>

$$\Delta S_{kj} > \sum_{i=1}^{n} \Delta S_{ki}\,, \tag{3}$$

<u>Policy Conflict</u>

$$\Delta S_{kj} \leq \bigcap_{i=1}^{n} \Delta S_{ki}\,, \tag{4}$$

where ΔS_{kj} describes the change in state vector for each strategy k (k = EO, TT, PP, IP, AL, PW, MT, FU, RE), j represents a combined set of k policies, which are comprised of single-policies i, up to a total number of n policies within each strategy (see **Table 15**). The nomenclature $\bigcap_{i=1}^{n} \Delta S_{ki}$ represents the mathematical "OR" logic where policy conflict occurs if the change in the overall model of the NBS vector value using a set of combined policies is less than any of the individual policies, i, comprising the cohort j.

Areas of policy synergy and conflict were compared to the reinforcing and balancing feedback loops from the CLD to better understand the implications and to explain them as a form of causal logic, elucidated with the aid of FCM-based scenario modelling.

3.2 National Spatial Data Infrastructure System

This section describes the development of NBS-Geo, an open-access web mapping application that gathers and integrates geospatial datasets from the social, ecological, environmental, and hydrologic domains using seamless, cloud-based data services throughout the contiguous United States. The tool's underlying data and system

architecture is described, and then the robustness of NBS-Geo is evaluated according to geospatial characteristics to better understand the tool's strengths, limitations, and suggestions for future research. The efficacy of the proposed platform is assessed to serve as a holistic data information system by exploring several characteristics associated with geospatial science, namely, openness, spatial functionality, scalability, and standardization. Recommendations are included for facilitating geospatial technologies to strengthen the amalgamation of broad co-benefits and multidisciplinary influences of natural systems.

In the resulting prototype, called NBS-Geo, comprehensive geospatial datasets associated with NBS co-benefits are curated from a cloud-based GIS server (described in **Section 3.2.2**) and delivered to users through a web-mapping application (described in **Section 3.2.3**). The web app contains capabilities for deriving rapid insight through value-added widgets (**Section 3.2.4**), including: 1) A time-series slider to analyze differences in land use projections, 2) A screening tool to analyze socio-demographic properties within the dynamic viewport, 3) A method for integrating local, high-resolution datasets with the national, cloud-based data layers, and 4) A geospatial toolbox for downloading select datasets toward local modeling and investigation. The NBS-Geo framework is presented as a means of representing overlapping characteristics of land use, environment, ecology, climate, hydrology, and society to encourage interdisciplinary data exploration.

3.2.1 System Architecture

Model architecture describes a combination of structural layout and functional capability of the webGIS platform (Agrawal and Gupta, 2017). A national information system is derived using cloud-based geospatial data layers that are seamless across the entire CONUS by extrapolating from Esri's ArcGIS Online service-oriented architecture. ArcGIS Online is an online gateway to cloud-based maps, layers, and data services,

whereby a user interface forms the basis for accessing an array of spatial datasets and functions. The ArcGIS online platform is leveraged to create a curated spatial mashup applicable to various NBS functionalities. The ensemble data mashup was derived from Esri's Living Atlas of the World data repository, which is an extensive collection of ready-to-use geospatial data layers from governmental, academic, and civil service users throughout the world. The Living Atlas uses REST servers to host and transfer the data layers, which may be accessed in the ArcGIS portal through a simple web uniform resource locator (URL) (Esri, 2021b). This geospatial architecture is demonstrated in **Fig. 9**.

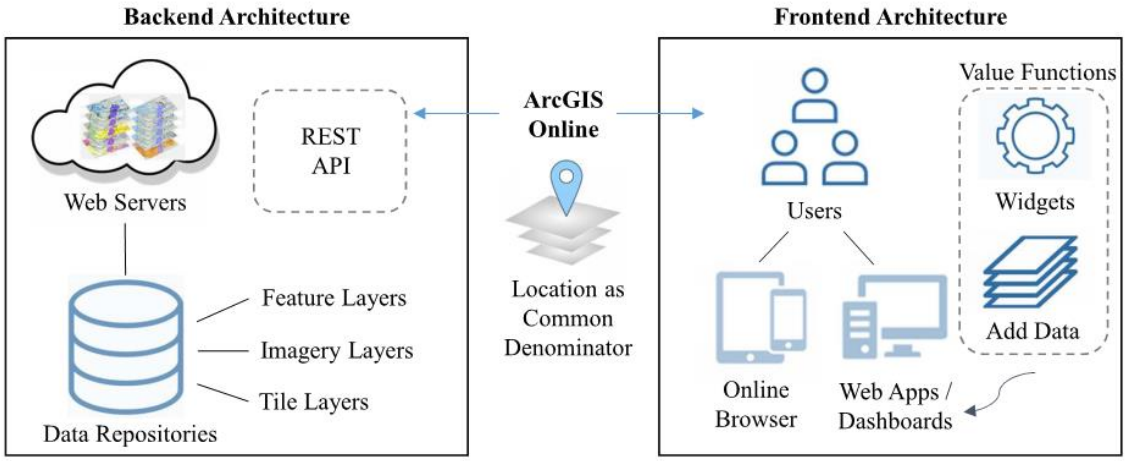

Fig. 9. NBS-Geo architectural framework.

3.2.2 Cloud-based Datasets

Representative geospatial layers were located within the Living Atlas data repository and curated for the NBS-Geo mapping application to encompass cross-domain NBS functionalities (**Table 5**). The data sources referenced from the Living Atlas cloud had been previously hosted by various governmental agencies, academic institutions, non-profit organizations, and geospatial corporations. The datasets selected for inclusion within NBS-Geo were categorized into the following themes: 1) NBS-multifunctionality, which

integrated various social, ecological, environmental, and hydrological co-benefits associated with NBSs, 2) Prediction, which comprised several projected data layers for supporting scenario analyses of future climatic and societal conditions in NBS planning, 3) Reference datasets, which were added to assist the user with general spatial grounding and further cross-domain spatial considerations, and 4) Hydrological datasets, encompassing watershed properties used in standard hydrological modelling schemes.

Each hosted data layer had been categorized within ArcGIS Online as authoritative, subscriber, or premium content. Authoritative content includes data from a national mapping agency or governmental entity that has been reviewed and vetted by Esri as reliable. Such content is recommended as the best-available data from the hosting agency and is proposed to be well-maintained over time. Subscriber content layers require an organizational subscription for access, including various satellite-based, large-scale data layers, demographical layers, and historical maps. An organizational subscription for Esri content is free, although many web users do not have organizational account access.

To eliminate this hindrance, and to provide NBS-Geo to the general public at no cost, the University of Houston's organizational account credentials were leveraged to pre-authorize subscriber content via the layer's source (i.e., the REST service endpoint) (Szukalski, 2021), thereby enabling use of the full web mapping application functionality without logging in to an Esri account. Premium content is subscriber content that consumes credits within the subscriber's organizational account. The only layer within NBS-Geo that had been categorized as premium content was the crime index. This data layer was pre-authorized through the University of Houston's organizational account to allow public access. Daily usage limitations of this dataset were then imposed within the web

application (Szukalski, 2021), which are only triggered when the crime index layer is selected for display, in order to minimize overall consumption of organizational subscription credits.

Table 5. Geospatial datasets included in the NBS-Geo web tool.

	Dataset	Attribution	Description
NBS Multifunctionality	Vegetation Index * ‡	U.S. Dept. of Agriculture (USDA)	High-resolution aerial imagery describing intensity of vegetation on the Earth's surface through the normalized difference vegetation index (NDVI).
	Open Spaces *	U.S. Geological Survey (USGS)	Open space lands protected by federal, state, and local governments, as well as private conservation easements.
	Intact Habitat Cores	Esri	National core index of minimally-disturbed natural areas, modeled as part of Esri's Green Infrastructure Initiative.
	Air Quality	National Aeronautics & Space Admin. (NASA)	Aggregated data in 50 km hexagonal bins of average annual particular matter (sized ≤ 2.5 micrometers, $PM_{2.5}$), in microgram/m^3, for years 1998-2016.
	Opportunity Zones	U.S. Department of the Treasury (DOT)	Qualified federal opportunity zones, per 2017 Tax Cuts and Jobs Act, for economic development in low-income neighborhoods.
	Social Vulnerability	U.S. Centers for Disease Control (CDC)	Social Vulnerability Index (SVI), created from U.S. census data to determine social vulnerability according to key themes: socio-economic, housing composition and disability, minority status and language, housing, and transportation.
	Health Statistics	University of Wisconsin	Composite county health rankings, including health behaviors (smoking, diet, and exercise), access to care, socio-economics, and life expectance.
	Urban Heat Islands *	The Trust for Public Land (TPL)	Relative heat severity during summers 2018 and 2019, from Landsat 8 imagery, ground-level thermal sensors.
	Building Footprints	OpenStreetMap	Building feature outlines from OpenStreetMap data, updated every minute.
	Soils Erodibility * ‡	U.S. Natural Resources Cons. Service (NRCS)	K-factor for national soil survey using Universal Soil Loss Equation.
	Crime Index * ϕ	Applied Geographic Solutions	Total crime score for 2020, including personal and property crime indices compared to national crime average.

Table 5 (continued):

	Dataset	Attribution	Description
Prediction	Temperature Anomaly	National Center for Atmo. Research (NCAR)	Projected anomalies for RCP 6.0 using mean results of future-scenario climate models. Anomalies represent average differences between years 2040-2059 compared with baseline conditions for 1986-2005.
	Precipitation Anomaly	National Center for Atmo. Research (NCAR)	
	Land Cover Change, Year 2050 ‡	Clark University	Predicted land cover for year 2050, projected from historical land cover patterns in the 2018-2018 European Space Agency Climate Change Initiative maps.
Reference Data	Environmental Facilities	U.S. Environmental Protection Agency (EPA)	Locations of facilities within the EPA Facility Registry Service (FRS), including brownfield sites, sources of pollution, superfund sites, radioactive sites, toxic release sites, greenhouse gas emitters, and power plants.
	Air Quality Monitors	U.S. Environmental Protection Agency (EPA)	Live (hourly) air quality data from local monitoring sites, displaying the average Air Quality Index (AQI).
	Stream Gauges *	U.S. Geological Survey (USGS) (and others)	Live stream gauge observations, including discharge and stage height.
	Flood Hazards ‡	Federal Emergency Mgmt. Assoc. (FEMA)	Federal flood insurance rate map special flood hazard area classifications.
	Dam Inventory	U.S. Army Corps of Engineers (USACE)	National inventory of dams, regulated by federal and state agencies, meeting large-scale or high-hazard potential classification criteria.
	Wetlands * ‡	Fish and Wildlife Service	National wetlands inventory with detailed characteristics of each area.
Hydrology	Rainfall * ‡	WorldClim	Average global mean precipitation from WorldClim, per interpolated rainfall stations, for 1970-2000 (mm).
	Soils Hydrology * ‡	U.S. Natural Resources Cons. Service (NRCS)	Hydrologic soil group classifications (A-D), depicting the rate of precipitation infiltration capability, from SSURGO soils data.
	Terrain Elevation * ‡	Various	Digital terrain elevation model showing ground height (m) from various sources, depending on highest-resolution available.
	Land Cover * ‡	National Land Cover Database (NLCD)	Time series of land cover (according to modified Anderson Level-II scheme), 2001-2016.
	Impervious Cover* ‡	National Land Cover Database (NLCD)	Time series of percent imperviousness, 30-m resolution.

*: authoritative content, ‡: subscriber content, ϕ: premium content

3.2.3 Sustainability Tool Framework

By linking users to holistic datasets through organizational web credentials, cloud-based data repositories are leveraged for improved integration of spatial data directly within environmental decision-making (Fu et al., 2019). Pre-assembled data servers alleviate the need to manually: 1) Search from a variety of diverse institutional websites and validate each source, 2) Download, extract, and compile numerous datasets, each with unique formats (i.e., ASCII, FTP, TIFF, LAS, XYZ, CAD, NetCDF, etc.), 3) Extract and mosaic the datasets to the study area, and 4) Process the layers into common projections and typologies for spatial analysis operations. The web map, and thus the referenced datasets, were hosted through the University of Houston ArcGIS organizational account to provide open access for all public visitors to the mapping website. Descriptive metadata was added to the NBS-Geo homepage (http://tinyurl.com/nbsgeohome) for proper accreditation and ease of locating the tool online through common keywords. A brief demonstration video was also created and linked to the NBS-Geo homepage to showcase the various user-friendly mapping features. The web map was then converted into a web application using the ArcGIS Web AppBuilder wizard, which involved selecting a pre-defined theme and customizing the user interface of the map with curated widgets. The cloud-based data layers within the web map were further categorized within the web app according to NBS functionality, reference datasets for spatial grounding, catchment datasets for hydrological modelling, and projected climate and land use datasets, as shown in **Fig. 10**. Detailed information for each layer was provided through the “More Info” link within the web-app ribbon, referencing URLs that describe the dataset authors, licenses of usage, background, symbols, and assumptions.

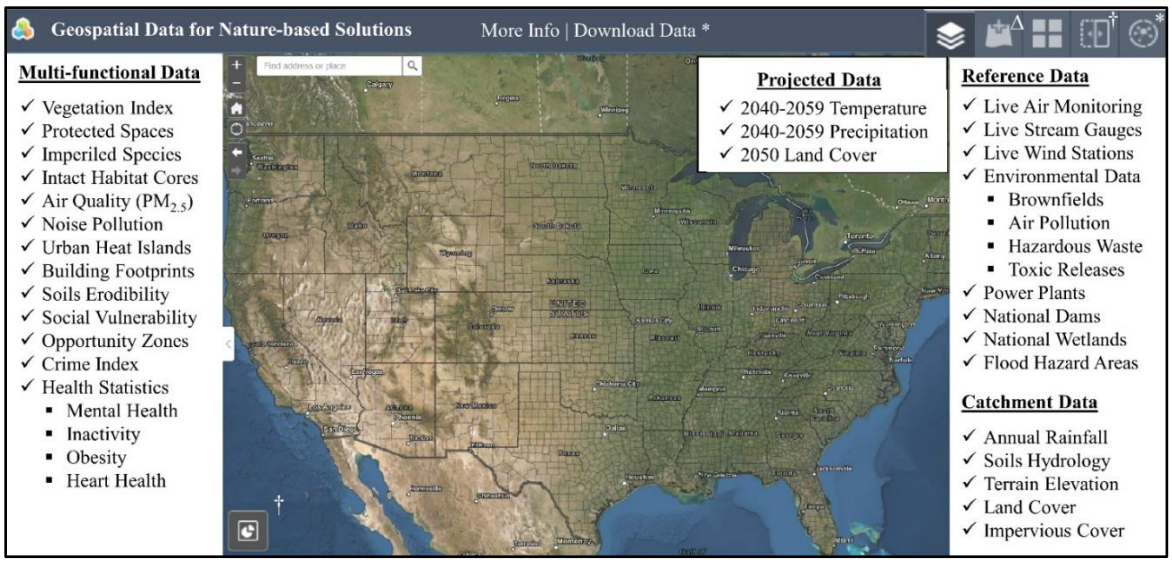

Fig. 10. Web user-interface for NBS-Geo.

3.2.4 Value-added Functions

A widget was added to the NBS-Geo ribbon (far-right icon, *, in **Fig. 10**) that allows users to download select extractable datasets, including live air monitoring, environmental facilities, power plant facilities, dams, air quality, social vulnerability, opportunity zones, and health statistics, to the user's computer according to a specified spatial boundary. For a featured data layer to be extractable within the ArcGIS Online platform, the data owner must have specifically enabled user-exportation capabilities. Many of the data layers pertinent to landscape analysis and hydrological modelling were not enabled for direct web-based extraction. Therefore, a tool called HMS-PrePro (Castro and Maidment, 2020) was adapted which connects the user with the Esri Living Atlas servers through temporary cloud-based feature images to extract pertinent datasets to the local computer according to a user-defined geospatial boundary. HMS-PrePro was designed for rapid pre-processing of cloud-based data layers into a format compatible with HEC-HMS hydrological software modelling. The capabilities of HMS-PrePro were used to leverage image server layer capabilities and aid in bridging the gap between robust datasets and the end-user through

cloud-based technologies. Several of the datasets available for extraction using the customized toolbox included: soils erodibility factor, soils hydrologic group, flood hazard areas, average precipitation, terrain elevation (low- and high-resolution), land cover (years 2016 and 2050), and impervious coverage. The "Download Data" link in the middle of NBS-Geo toolbar (*) (**Fig. 10)** routes the user to a GitHub repository containing the ArcMap Toolbox for data download.

Additional added-value widgets were included in the web application, as identified in **Fig. 10** with the (†) symbol. The bottom-left (†) icon represents a screening widget customized to allow visual exploration of various social vulnerability themes and their respective compositions within the user viewport. In the top-right toolbar of NBS-Geo, a sliding tool widget was added (†) for exploring the spatial differences between current and projected land cover classifications. This toolbar also includes an added-value widget, identified with the (Δ) symbol, to allow uploading of user-defined geospatial data layers into the web mapping application for locally-curated visualization. For example, if a jurisdiction possessed higher-resolution datasets than what is contained within the Esri Living Atlas server, the end-user could easily add their own geospatial data layers to the web mapping application for a fully customized assessment of local conditions. By utilizing such added-value widgets and tools, we transition from a large assortment of disparate geospatial datasets toward increased knowledge and user-derived wisdom.

3.2.5 Suitability Evaluation

Here, the applicability of NBS-Geo is evaluated as a robust data system and web mapping prototype for planning and researching NBSs across disparate domains. To this end, the extent to which NBS-Geo supports common GIS metrics of usability and reliability are analyzed, namely: 1) Openness, 2) Spatial Analysis Functionality, 3)

Scalability, and 4) Geospatial Standards. Recommendations for how improved geospatial web applications and data technologies could facilitate such goals are summarized in **Section 4.2.1**. This work builds upon the work presented by Choi et al. (2016), where the authors assessed the applicability and effectiveness of a national spatial data information (NSDI) system to progress urban sustainability rooted in equitable principles. In this study, Choi et al. (2016) proposed a qualitative evaluation of three common characteristics associated with geospatial systems. First, a robust NSDI must contain a high degree of openness to encourage collaboration amongst public and private domains and improve widespread accessibility (Paradis, 2020). Second, the system should foster an ability for functional spatial analysis through streamlined formats and value-added data attributes. Finally, the geospatial standards associated with the NSDI must be consistent, easily accessible, combinable, and interoperable across platforms. This approach is extended to also consider the suitability of a NSDI framework for use across nested spatial scales, as suggested by the UN Intergovernmental Panel on Climate Change (IPCC) regarding NBSs and data science (Frantzeskaki et al., 2019).

3.3 Framework for Equity-based Optimization

In this section, 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 transdisciplinary characteristics. Specifically, this study explores 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). The statistical dispersion of social vulnerability is then identified 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, further described in **Section 3.3.4**.

3.3.1 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 across space, as represented in **Fig. 11**.

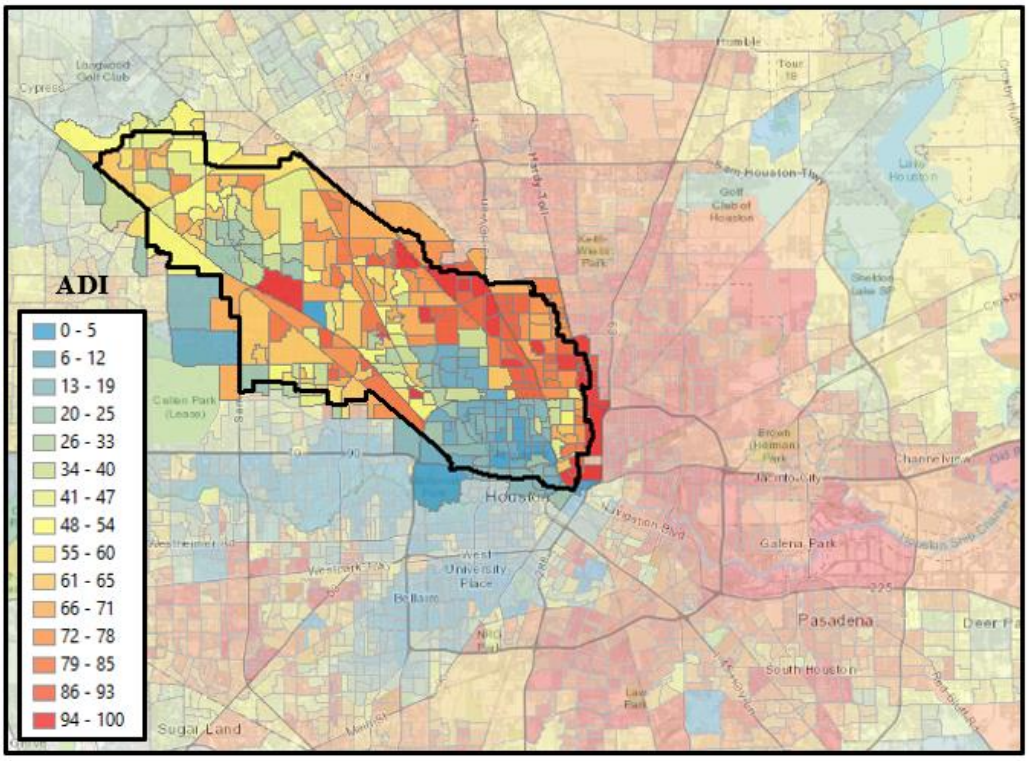

Fig. 11. Area deprivation index of White Oak Bayou watershed.

3.3.2 Hydro-environmental SWMM Model

3.3.2.1 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 were 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 are summarized in **Table 6**, which were used to develop intensity-duration-frequency (IDF) curves in PCSWMM for varying annual exceedance probability (AEP) storm events. 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). PCSWMM translates the IDF curve of each subcatchment into a synthetic rainfall distribution for estimating peak flow and total runoff volume, as depicted in **Fig. 12**.

Table 6. 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
500-Year (0.2% AEP)	54.26	2.72	0.5129

The design rainfall intensity I (inches/hour) is calculated according to

$$I = \frac{b}{(t_c + d)^e}, \tag{5}$$

where $b, d,$ and e are coefficients from the NOAA frequency-duration curves, and t_c is the time of concentration for each subcatchment in minutes.

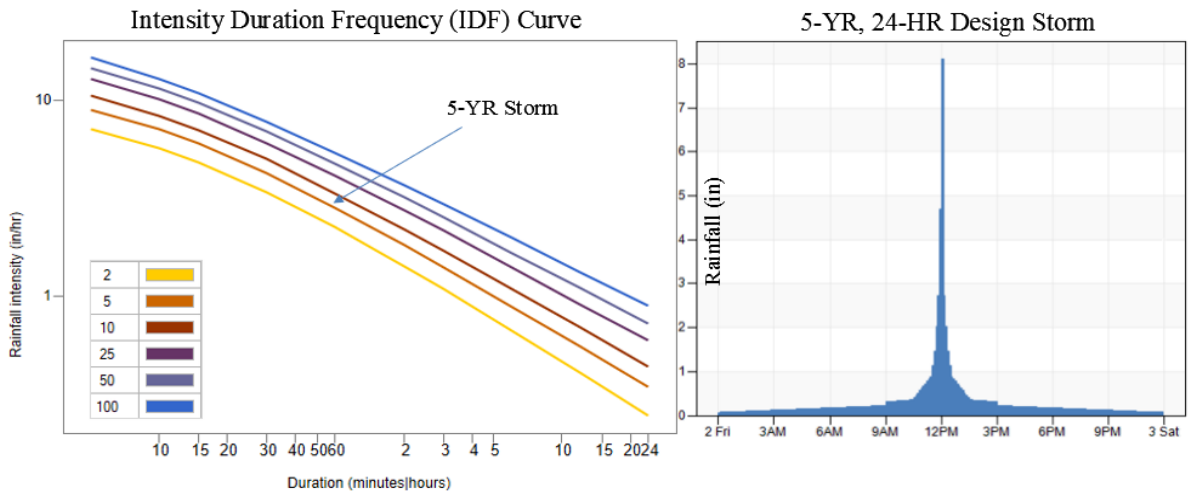

Fig. 12. IDF curve and synthetic design storm for the White Oak Bayou watershed.

3.3.2.2 Pollutant Load Modeling

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

$$EMC_s = \frac{\int C_s Q_s \, dt}{\int Q_s \, dt}, \tag{6}$$

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 (in cfs) for each subcatchment, s, changing over the time of simulation, 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 3.3.3**), 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 7**. 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).

Table 7. Pollutant load parameters for modeling total suspended solids (TSS).

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

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, as shown in **Table 7**. The removal efficiencies for each of the NBS types modeled in this study were obtained from the 2020 International Stormwater BMP Database (Clary et al., 2020), which corresponded well with average removal efficiencies in the NBS literature for watershed-scale stormwater modeling (e.g., Eckart et al. (2017); Liu et al. (2015)).

3.3.2.3 NBS Water Balance Modeling

EPA's SWMM engine calculates the water balance for NBS-driven systems using a nonlinear reservoir model 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. 13** (Rossman and Huber, 2016).

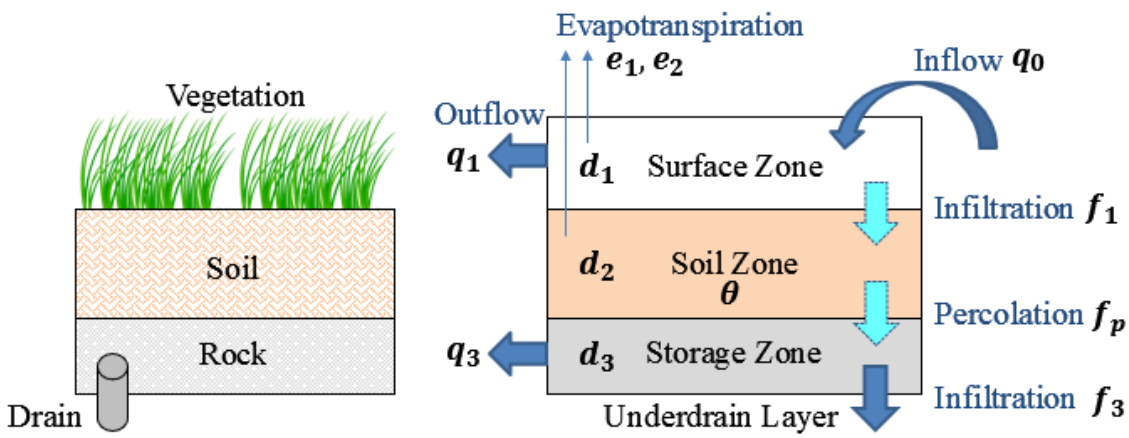

Fig. 13. Conceptual model of NBS water balance processes.

The water fluxes are defined by:

$$\frac{\partial d_1}{\partial t} = q_0 - e_1 - f_1 - q_1, \tag{7}$$

$$d_2 \frac{\partial \theta}{\partial t} = f_1 - e_2 - f_\mathrm{p}, \tag{8}$$

and

$$\frac{\partial d_3}{\partial t} = f_p - f_3 - q_3, \tag{9}$$

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.

This 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 described in **Table 8** 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.

Table 8. 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	

Various input parameters are also required within a SWMM model (e.g., conductivity rate, vegetation volume, clogging properties, surface roughness, etc.) to depict the engineered design of local NBS features, which were obtained from the City of Houston design guidelines for low impact development (COH, 2019b), as summarized in **Table 9**.

.

Table 9. Parameter controls for NBS design in Houston, Texas, USA.

	Parameter	NBS Feature			Units
		Bioretention Cells	**Porous Pavement**	**Tree Boxes**	
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

3.3.2.4 Calibration & Validation

The hydrological basin parameters were calibrated to observed streamflow measurements for 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. 14**.

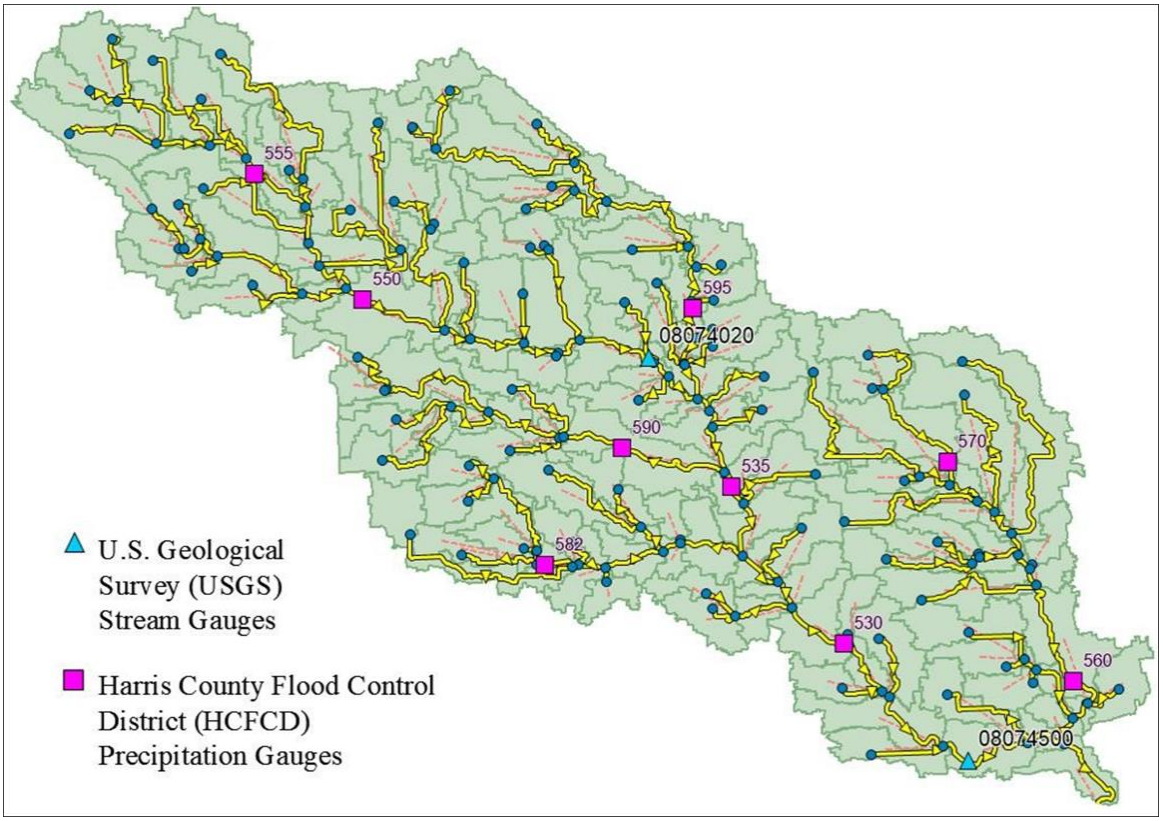

Fig. 14. PCSWMM basin model, stream gauges, and precipitation gauges for WOB.

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, resulting in ten unique storm events for calibration and eight unique storm events for validation, as demonstrated in **Fig. 15**. 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. 16**. The basin model was simulated with the calibrated parameters and compared to observed streamflow and resulting error metrics to measure goodness-of-fit.

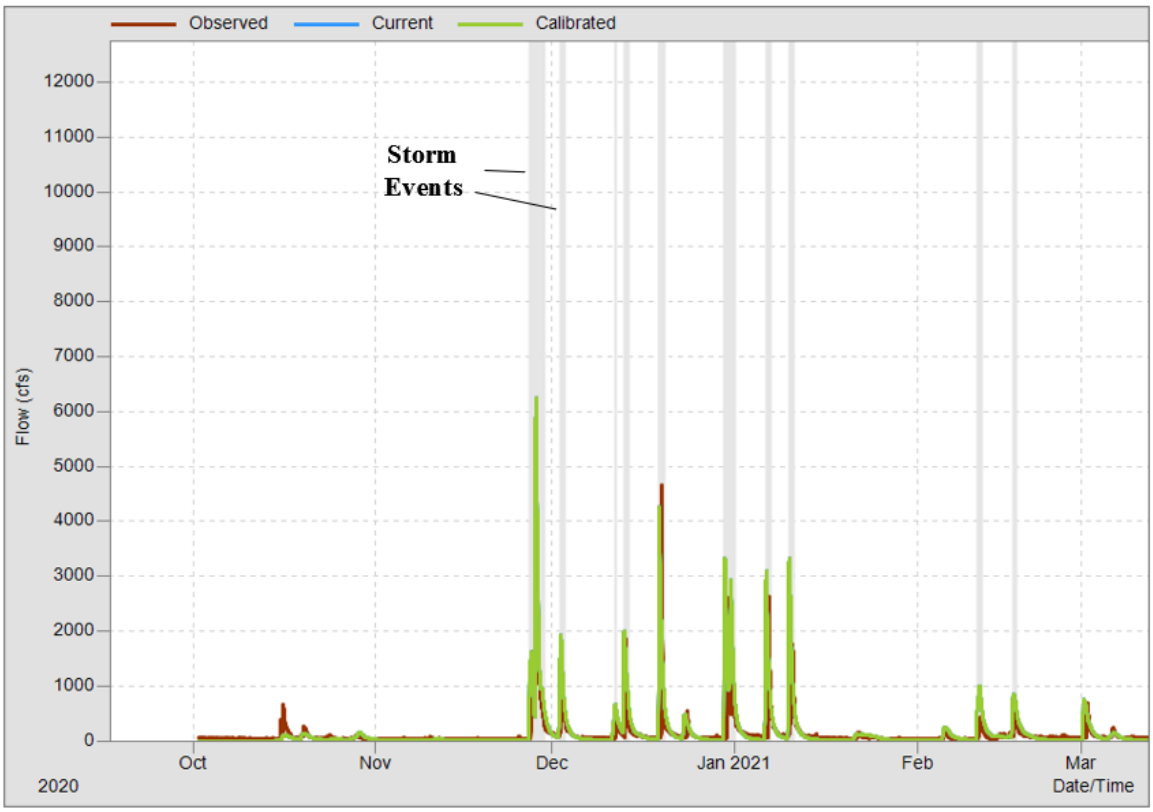

Fig. 15. PCSWMM SRTC storm event selection.

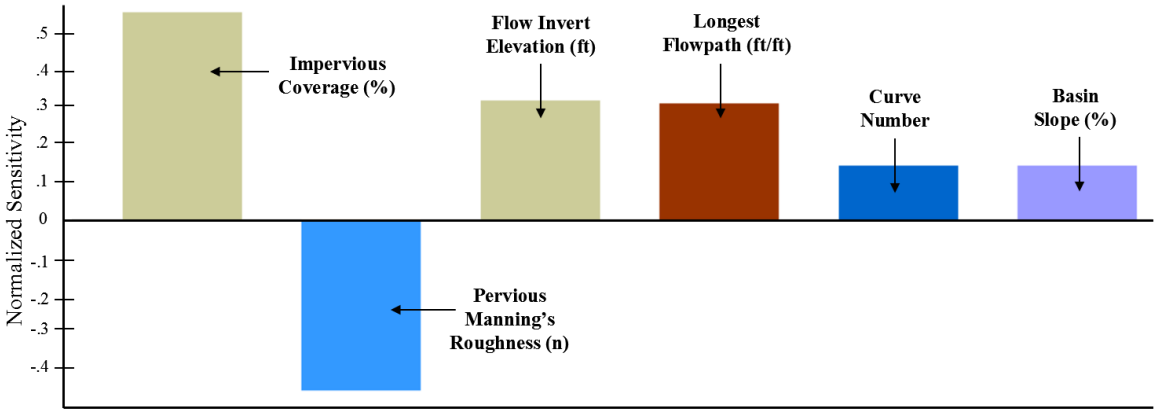

Fig. 16. Normalized sensitivity analysis output for primary variables.

The error metric employed in this study was the integrate 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 by

$$ISE = \frac{\sqrt{\sum\left(y_{obs}^{i} - y_{comp}^{i}\right)^{2}}}{\sum y_{obs}^{i}}, \tag{10}$$

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 from "poor" to "excellent", according to **Table 10** (Sarma et al., 1973).

Table 10. Integral square error (ISE) numerical scores and rating classifications.

Rating	ISE
Excellent	< 3
Very Good	3 - 6
Good	6 – 10
Fair	10 – 25
Poor	> 25

The model calibration and validation hydrographs and ISE error metrics are demonstrated in **Fig. 17 - Fig. 18** and **Table 11** – **Table 12**, respectively.

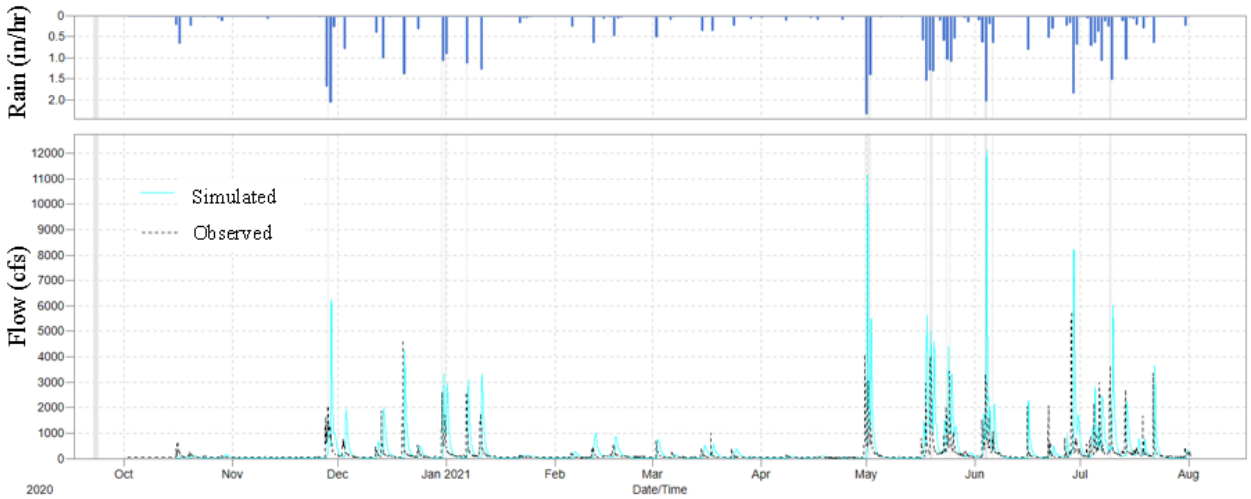

Fig. 17. Calibration output hydrographs for USGS Gauge No. 08074500.

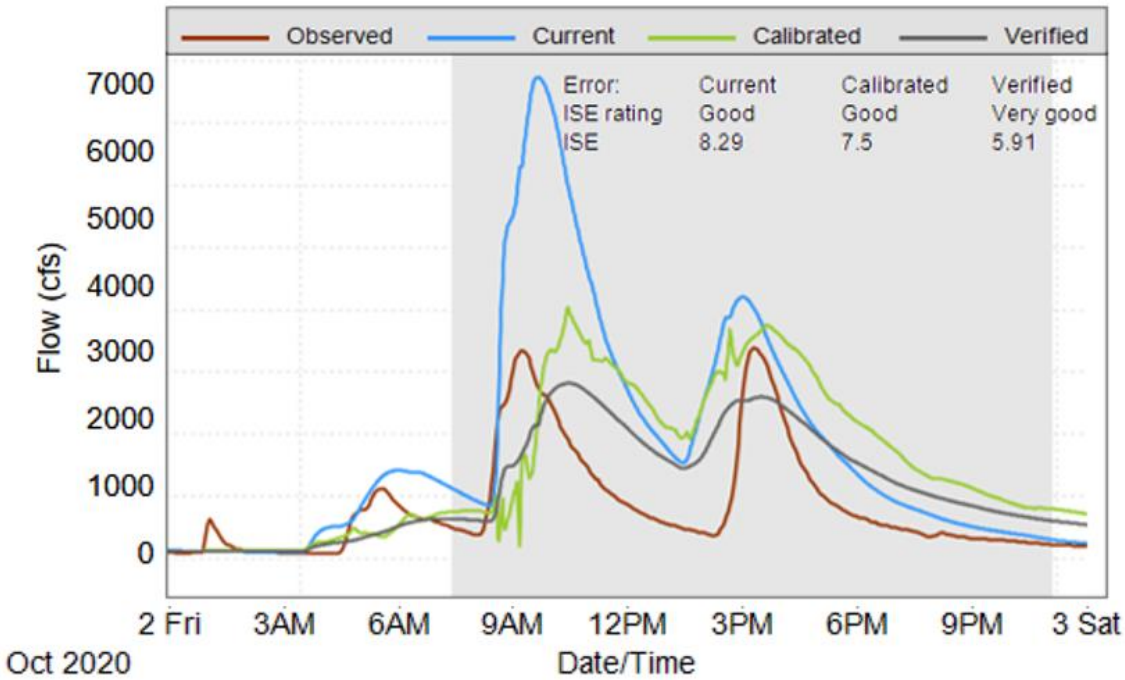

Fig. 18. Validation output hydrographs for storm event Mar. 2021 to Aug. 2021.

Table 11. 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 12. 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)

3.3.3 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. 21**, adapted from (SFEI, 2018). 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: 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).

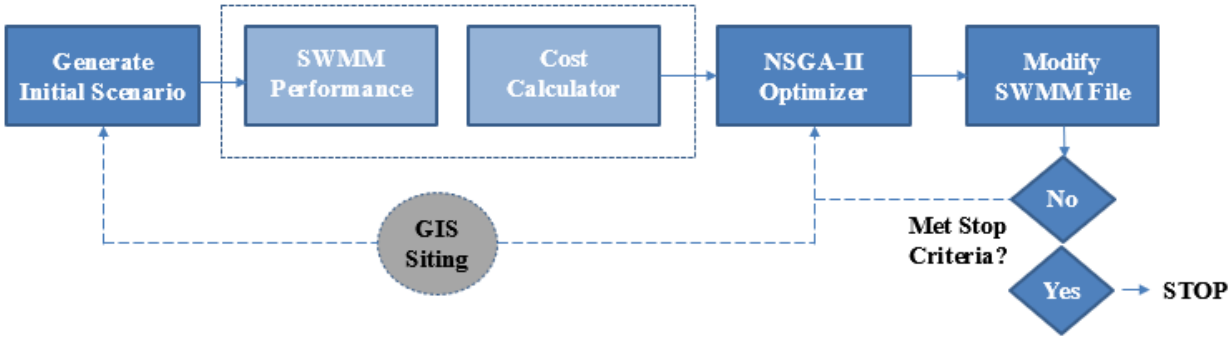

Fig. 19. GreenPlan-IT optimization workflow.

The GIS-based SLT was used to identify all potential locations of NBS features within the WOB watershed, as shown in **Fig. 20**. 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). The SLT locations were summarized according to subcatchment and used as input for the GreenPlan-IT Optimization Tool, as detailed in **Appendix B**.

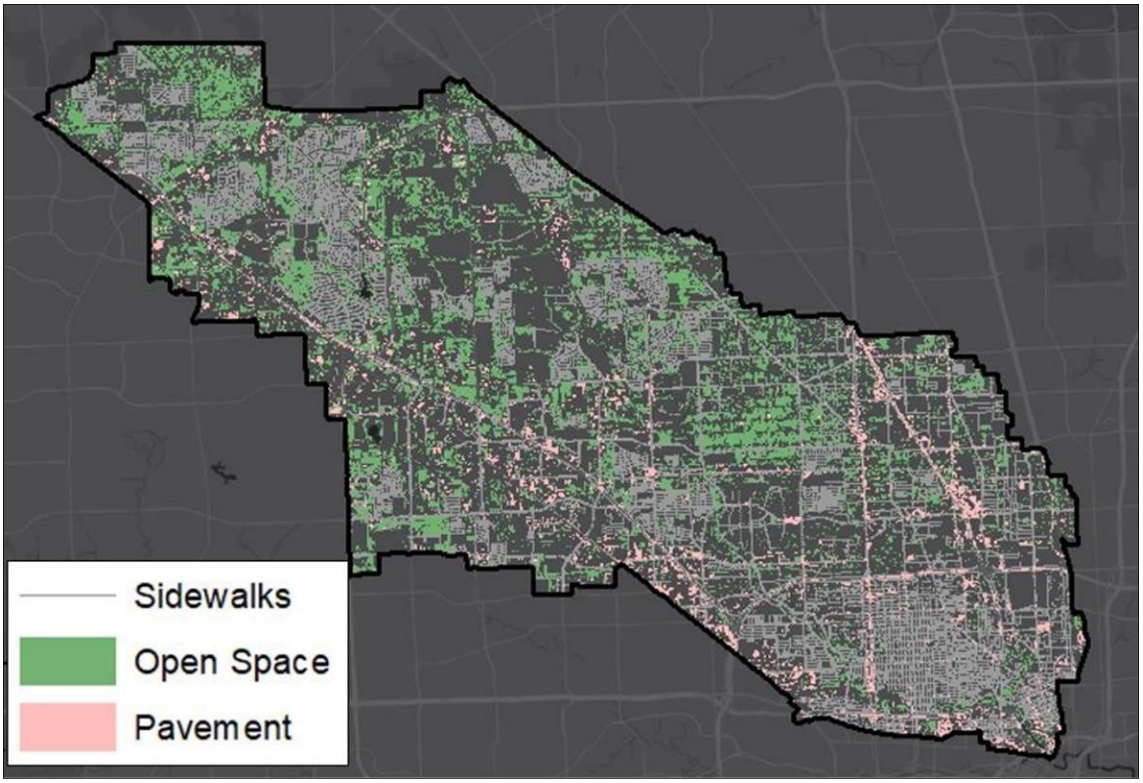

Fig. 20. Geospatial siting of potential NBS locations in the WOB watershed.

Baseline flows and TSS loads were quantified within the SWMM model for various design storm events, as described in **Section 3.3.2**. The SLT output then served as a spatial constraint for the GreenPlan-IT optimization tool, which executes several hundred SWMM models according to unique spatial allocations of NBS features within the permissible areas (i.e., the shaded areas shown in **Fig. 210**). 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.

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 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 GreenPlan-IT tool contains a threshold of 200 generations, each with a population size of 100, for a maximum of 20,000 watershed simulations (SFEI, 2018). The model outputs are plotted as a function of cost (x-axis) versus runoff or load reduction (y-axis), resulting in a Pareto curve (see **Section 4.3.1**). 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).

3.3.4 Multi-objective Gini Coefficient

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. 21**, 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. 21**. 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), **Fig. 21**.

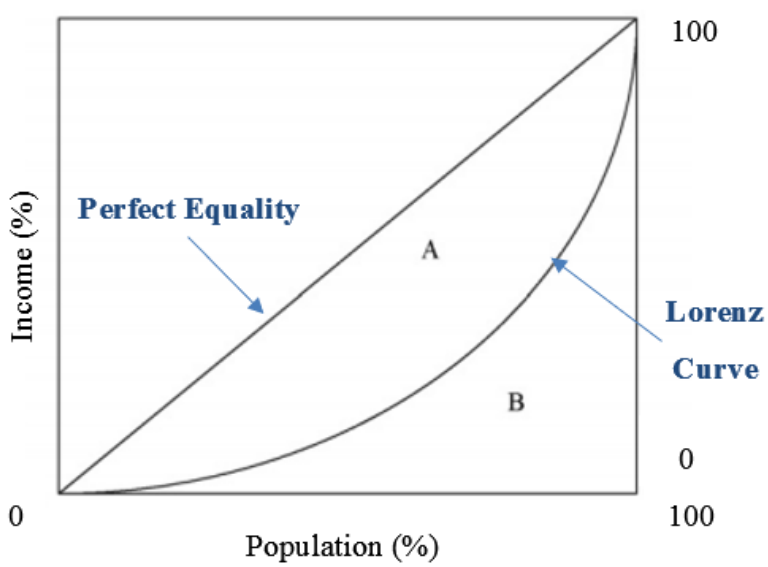

Fig. 21. Conceptual graph of Gini-based equality and Lorenz curve.

The Gini coefficient (G) is expressed graphically by

$$G = \frac{A}{(A + B)}, \tag{11}$$

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

$$G_i = 1 - \sum_{i=1}^{n} (Y_i - Y_{i-1})(X_i + X_{i-1}), \tag{12}$$

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 (D. 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 was optimized using the Gini index and a multi-criteria assessment of land, population, income, and environmental capacity. In Sun et al. (2010), the conflict between wastewater efficiency and social equality was bridged by balancing tradeoffs between various policy-making goals amidst limited resources.

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 efficiency 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. To my knowledge, this is the first attempt to utilize the Gini coefficient for optimizing allocation of NBSs according to combined social equity and hydro-environmental efficacy. 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:

$$\omega_s = \sum_{j=1}^{n} z_{js} A_j \,, \tag{13}$$

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),

$$\eta_s = \frac{\left(\frac{a_s - b_s}{a_s}\right) * 100}{\sum_{j=1}^{n} z_{js} A_j c_j}, \tag{14}$$

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.

$$\mu_s = \frac{ADI_s}{\sum_{s=1}^{m} \omega_s}, \tag{15}$$

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

$$\tilde{x} = \frac{x - x_{min}}{x_{max} - x_{min}} * 100, \tag{16}$$

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 Lorenz curve and Gini coefficient is then calculated by **Eq. (17)-(19)**:

$$Y_s = Y_{s-1} + \frac{\widetilde{\omega_s}}{\sum_{s=1}^{m} A_s} * 100, \tag{17}$$

$$X_s = X_{s-1} + \left(\frac{\widetilde{\eta_s}}{\sum_{s=1}^{m} \widetilde{\eta_s}}\right) * 100, \tag{18a}$$

$$X_s = X_{s-1} + \left(\frac{\widetilde{\mu_s}}{\sum_{s=1}^{m} \widetilde{\mu_s}}\right) * 100, \tag{19b}$$

and

$$G_i = 1 - \sum_{s=0}^{m} \left(X_s - X_{(s-1)}\right)\left(Y_s - Y_{(s-1)}\right), \tag{20}$$

where Y_s is the y-axis value on the Lorenz curve, X_s is the x-axis value on the Lorenz curve (**Eq. 18a** is the X_s value for the hydrologic and pollutant load efficiency indicators, and

Eq. 18b is the X_s value for the social deprivation indicator), 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

$$Optimization\ Objective: \min\left(\frac{\sum_{i=1}^{I} G_i}{I}\right), \tag{21}$$

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 according to **Eq. (13)-(18)**,
3. Plot the Lorenz curves and calculate each G_i using **Eq. (11)** or **Eq. (19)**,
4. Aggregate the objective functions and compare Lorenz curves according to the multi-criteria Gini coefficient, **Eq. (20)**,
5. Identify the greatest distribution of social equality and hydro-environmental efficiency by minimizing the objective function in **Eq. (20)**.

4. RESULTS & DISCUSSION

4.1 Policy Coherence Embedded in Feedback Loops

4.1.1 Identification of Variables

The stakeholders nominated 26 total variables, which were optimized within *Vensim* to reveal 19 unique variables and 37 causal links. These results corresponded well with the average number of variables (n=23) and connections (n=37) observed in typical FCMs, according to the meta-study by Özesmi and Özesmi (2004). Interesting insights from the group stakeholder session included unique trade-offs associated with the group understanding of NBS socio-institutional barriers compared with the general consensus within the NBS literature. Several institutional barriers were suggested by the group that were not generally found within the NBS literature, such as a general opinion that regulations at the state and federal level strongly hindered NBS implementation ability. Moreover, the stakeholders did not associate co-benefits with an improved capability of implementation in this locale, which has been strongly linked within the NBS literature. Other surprising insights from the workshop included a robust debate regarding how increased vegetation within the urban fabric is not necessarily desired by local constituents, as a lack of maintenance had promoted habitat overgrowth, leading to pests, rodents, and other nuisances. Other contradictions between stakeholder-identified variables within the group discussions were noted, including conflicting perceptions about the efficacy of local design specifications, community will, stormwater mitigation, and decision-making frameworks. Interestingly, the GMB discussions suggested a culture that was predisposed to working in silos, yet the stakeholders were not keen to list this as a barrier associated with NBS growth. The stakeholders demonstrated difficulty in defining the term ‘political

will', although all agreed this factor was extremely important for NBS efforts. Such discrepancies highlight the importance of understanding local conditions and clarifying stakeholder insights when assessing causal feedbacks and policy dynamics regarding complex socio-ecological issues. To aid in validating the CLD, several participants requested clarification of variable meanings and roles. Therefore, each variable was uniquely defined to represent the group's collective understanding (**Table 13**) and emailed to the stakeholders for use during the CLD validation phase.

Table 13. Definition of socio-institutional factors associated with NBS adoption.

No.	Variable	Definition
1	Climate Intensification	Intensification of extreme climate events, including urban heat, air quality reduction, greenhouse gas emissions, and rainfall patterns (leading to flooding).
2	Community Buy-in	Reduced public fears regarding perceived risks/nuisances of NBSs. Local neighborhoods and developers excited to implement NBSs. Grassroots efforts toward more NBS projects. Community involvement in NBS taskforces and politics. Neighborhood workshops. Dialogue within civil groups.
3	Educational Outreach	Outreach programs targeted at improving community perception and understanding of NBS functionality and co-benefits. Includes media reporting. Targeting strategic citizen involvement in the selection, planning, funding, and maintenance of NBSs.
4	External Grants	Enhanced partnerships across institutions, including academia, local-regional, state, federal toward winning NBS grants.
5	External Regulations / Laws	Funding requirements/incentives and regulatory requirements to prove multiple co-benefits beyond stormwater mitigation at the state and federal level.
6	Habitat Growth	Vegetation overgrowth into swamp-like conditions, including unwanted pests, rodents, and other invasive species, due to lack of maintenance of NBS projects.
7	Incentives Programs	Incentives for local development. Subsidies, grants, loans, fee reductions, incorporated into local development plans (includes federal and state subsidies).
8	Increased Development	Encompasses population growth, reduced land space, building "up", more tax revenue, and less natural pervious coverage.

Table 13 (continued):

No.	Variable	Definition
9	Local Advocates & Leaders	Local staffing for NBS funding, regulations, trans-institutional partnerships. Designated champion(s) with resources to make change. Central, singular, NBS department that is integrated across sectors and separate from other utilities.
10	Local Funding	Combined funding sources for public implementation of NBSs. Local non-profits, local capital improvement project funding, ear-marked drainage tax revenue. Understanding that hybrid NBSs are cheaper than grey-infrastructure. Quantifying co-benefits as economic/health benefits in cost-benefit analyses.
11	Local Political Will	Transition from reliance on traditional engineering (grey systems) to hybrid (green-grey) approaches. Increase of institutional urgency for more NBSs. Increased inter-agency cohesion for green projects.
12	Local Regulation	Design and implementation regulations that are less stringent than grey-water. Clear legal guidelines (no conflicting provisions). Rapid permitting. Long-term maintenance regulations. Regular site inspections. Mandatory green space allowance for new and retrofit construction projects.
13	Maintenance Programs	Technical capacitance for green maintenance; designated O&M funds; partnership with developers, contractors, and public residents for long-term ownership.
14	Nature-based Solutions	Increase in implementation of NBSs, including urban-type (e.g., green roofs, rain barrels, bioswales, pervious pavement) and best-management practices (e.g., bioretention ponds).
15	Pilot Projects	Community NBS projects funded and promoted by local government. Includes tours, educational signage, press coverage.
16	Population Growth	Increase in local population, resulting in changes of land use type, impervious coverage, equity.
17	Social Equity	Clear frameworks for capacitance building in vulnerable and marginalized communities with reference to NBSs.
18	Technical Training	Design and maintenance training of engineers, environmental consultants, and governmental staff. Support of local expertise certifications (i.e., LEED). Additional workshops and trainings. Limited staff turnover with NBS expertise.
19	Visualization of Co-benefits	Accepted understanding of NBS benefits that extend beyond stormwater quantity and quality (air quality, health, recreation, crime, noise). Visualizing how NBSs impact one's backyard.

4.1.2 Causal Loop Diagram and Feedback Loops

The final causal loop diagram from the GMB exercise and stakeholder validation is depicted in **Fig. 22**. Reinforcing loops propagate the direction of change within the system, which would theoretically continue to grow (or decrease) over time as one linked variable is altered. Conversely, balancing loops counteract the direction of change and transition the system toward states of equilibrium. From the CLD model, four primary reinforcing loops and two balancing loops were identified. Reinforcing loop **R1** was noted as the "Maintenance Loop", whereby improved maintenance (from local regulations) would ideally reduce habitat over-growth and improve community buy-in of NBS technologies, spurring political will and additional local regulations. Reinforcing loop **R2**, the "Funding Loop", was identified as an opportunity to increase NBSs by using local funds to implement more pilot projects, enhance visualization of co-benefits, and strengthen community buy-in. The reinforcing loop **R3**, "Community Loop", describes the general stakeholder belief that enhanced external regulations would drive local regulation, negating the need for local incentives programs (which were observed to have a negative effect on community buy-in due to their volunteering nature), which in turn would drive additional local political will, feeding into the overall political will of the federal and state governmental constructs. Reinforcing loop **R4**, the "Advocacy Loop", describes the condition where local political will could be used to increase the amount and influence of local advocacy departments and NBS champions, thereby driving implementation of additional pilot projects, trainings, and outreach to bolster community acceptance. The balancing loop **B1**, "Climate Loop", was identified as an opportunity to balance the system of NBS implementation upon achieving a desirable level of climate mitigation (e.g., urban heat regulation, stormwater flow abatement, water quality enhancement, carbon

sequestration), depending on local goals and conditions. The balancing loop **B2**, "Equity Loop", was observed as an opportunity to counteract the negative impacts of population growth (and thus increased levels of non-pervious development) while also improving community buy-in. These overarching themes were used to drive the assessment of causal feedbacks and their influence on policy effectiveness, further described in **Section 4.1.3**.

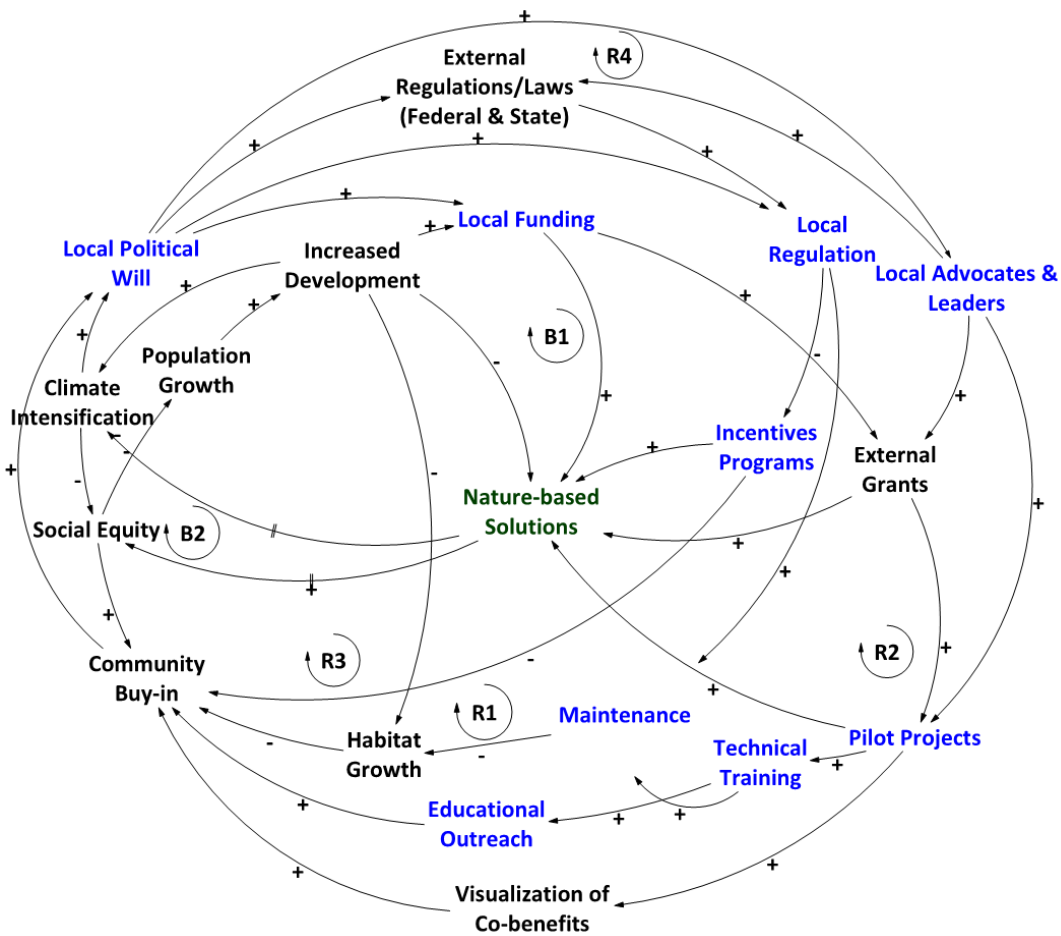

Fig. 22. Stakeholder-derived causal loop diagram.

Table 14 summarizes the feedback loops and their average strengths. The average strengths were adapted from FCM definitions for weighted in-degree and out-degree (Özesmi and Özesmi, 2004), given by

$$w_f^{(t=0)} = \pm \frac{\sum_{i=1}^{M} \sum_{j=1}^{M} |w_{ij}|}{M}, \tag{22}$$

where w_f describes the average strength of each feedback loop f, w_{ij} is the stakeholder-defined strength between variable i and j in the loop, and M is the total number of unique connections within the loop. The causal strength is then assigned a polarity of '+' for reinforcing loops and '-' for balancing loops.

Table 14. Balancing and reinforcing feedback loops.

Loop	Variable Connectivity & Feedback Strengths	(w_f)
R1	Local Political Will $\xrightarrow{\mathbf{+0.75}}$ Local Regulation $\xrightarrow{+0.50}$ Maintenance $\xrightarrow{-0.75}$ Habitat Growth $\xrightarrow{-0.25}$ Community Buy-in $\xrightarrow{+0.50}$ Local Political Will	0.35
R2	Local Political Will $\xrightarrow{\mathbf{+0.75}}$ Local Funding $\xrightarrow{+0.25}$ External Grants $\xrightarrow{+0.75}$ Pilot Projects $\xrightarrow{+0.50}$ Visualization of Co-benefits $\xrightarrow{+0.50}$ Community Buy-in $\xrightarrow{+0.50}$ Local Political Will	0.54
R3	Local Political Will $\xrightarrow{\mathbf{+0.25}}$ External Regulations / Laws $\xrightarrow{+0.75}$ Local Regulation $\xrightarrow{-0.25}$ Incentives Programs $\xrightarrow{-0.25}$ Community Buy-in $\xrightarrow{+0.50}$ Local Political Will	0.40
R4	Local Political Will $\xrightarrow{\mathbf{+0.50}}$ Local Advocates $\xrightarrow{+0.25}$ Pilot Projects $\xrightarrow{+0.25}$ Technical Training $\xrightarrow{+0.25}$ Educational Outreach $\xrightarrow{+0.25}$ Community Buy-in $\xrightarrow{+0.50}$ Local Political Will	0.33
B1	Local Political Will $\xrightarrow{\mathbf{+0.75}}$ Local Funding $\xrightarrow{+0.50}$ Nature-based Solutions $\xrightarrow{-0.50}$ Climate Intensification $\xrightarrow{+0.50}$ Local Political Will	- 0.56
B2	Social Equity $\xrightarrow{\mathbf{-0.25}}$ Population Growth $\xrightarrow{+0.75}$ Increased Development $\xrightarrow{+0.25}$ Local Funding $\xrightarrow{+0.25}$ Nature-based Solutions $\xrightarrow{+0.50}$ Social Equity	- 0.40

Naturally, the feedback loop weights will change during the dynamic simulation as the loops are influenced by other loops and variables over time. However, by identifying the initial feedback loop strengths according to **Eq. (21)**, it becomes possible to complement our understanding of the FCM-based scenario results with insights regarding loop dominance, as well as shifts in loop dominance, according to how the loops inter-relate within the system.

4.1.3 Policy effectiveness and causal logic

The dynamics of the system resulted in a positive increase in the state of the NBS variable for all of the modeled management strategies. The relative change in NBS implementation for each strategy (n =1,2,3) is shown in **Table 15** as a percentage (ΔS_k). Typically, when performing FCM-based scenario modeling for policy assessment, the change in the end-state vector for the goal variable is calculated as the difference between the baseline-scenario and the strategy-scenario. In such cases, the baseline scenario is defined as the state vector of the model when all driver variables (i.e., variables that have no input feedbacks) are clamped to a value of +1.00 (Singh and Chudasama, 2020). However, the FCM model for this study had no driver variables, meaning all variables were ordinary and contained both input and output feedbacks (Özesmi and Özesmi, 2004), therefore the baseline NBS state vector was null (ΔS_{NBS} =0). As such, ΔS_k represents the state vector value for the NBS variable after each policy, or set of policies, was modeled within the *Mental Modeler* scenario-builder, expressed as a percentage.

Table 15. Fuzzy cognitive mapping-based scenarios.

	ki	ΔS_{ki}		kj	ΔS_{kj}	kj	ΔS_{kj}	kj	ΔS_{kj}
1 Policy (n = 1)	EO	9%	2 Policies (n = 2)	EO-TT	11%	TT-IP	18%	PP-MT	51%
	TT	5%		EO-PP	52%	TT-AL	39%	*PP-FU	84%
	PP	48%		EO-IP	21%	TT-PW	56%	PP-RE	47%
	IP	12%		EO-AL	41%	TT-MT	7%	IP-AL	50%
	AL	36%		EO-PW	56%	TT-FU	66%	IP-PW	74%
	PW	56%		EO-MT	13%	TT-RE	3%	IP-MT	18%
	MT	5%		EO-FU	66%	PP-IP	60%	IP-FU	76%
	*FU	65%		EO-RE	8%	PP-AL	60%	IP-RE	16%
	RE	0%		TT-PP	50%	PP-PW	76%	AL-PW	68%

Table 15 (continued):

	kj	ΔS_{kj}		kj	ΔS_{kj}	kj	ΔS_{kj}
2 Policies (n = 2)	AL-MT	39%	3 Policies (n = 3)	EO-PW-MT	56%	PP-IP-RE	62%
	AL-FU	81%		EO-PW-FU	73%	PP-AL-PW	79%
	AL-RE	35%		EO-PW-RE	55%	PP-AL-MT	61%
	PW-MT	56%		EO-MT-FU	67%	PP-AL-FU	88%
	PW-FU	73%		EO-MT-RE	10%	PP-AL-RE	58%
	PW-RE	55%		EO-FU-RE	63%	PP-PW-MT	76%
	MT-FU	66%		TT-PP-IP	62%	PP-PW-FU	85%
	MT-RE	2%		TT-PP-AL	61%	PP-PW-RE	75%
	FU-RE	62%		TT-PP-PW	76%	PP-MT-FU	84%
3 Policies (n = 3)	EO-TT-PP	53%		TT-PP-MT	51%	PP-MT-RE	48%
	EO-TT-IP	24%		TT-PP-FU	84%	PP-FU-RE	82%
	EO-TT-AL	42%		TT-PP-RE	48%	IP-AL-PW	81%
	EO-TT-PW	56%		TT-IP-AL	53%	IP-AL-MT	53%
	EO-TT-MT	14%		TT-IP-PW	64%	IP-AL-FU	88%
	EO-TT-FU	67%		TT-IP-MT	20%	IP-AL-RE	52%
	EO-TT-RE	9%		TT-IP-FU	77%	IP-PW-MT	74%
	EO-PP-IP	64%		TT-IP-RE	19%	IP-PW-FU	84%
	EO-PP-AL	63%		TT-AL-PW	68%	IP-PW-RE	74%
	EO-PP-PW	76%		TT-AL-MT	40%	IP-MT-FU	77%
	EO-PP-MT	54%		TT-AL-FU	81%	IP-MT-RE	18%
	EO-PP-FU	84%		TT-AL-RE	37%	IP-FU-RE	77%
	EO-PP-RE	50%		TT-PW-MT	56%	AL-PW-MT	68%
	EO-IP-AL	55%		TT-PW-FU	73%	AL-PW-FU	80%
	EO-IP-PW	74%		TT-PW-RE	42%	AL-PW-RE	67%
	EO-IP-MT	27%		TT-MT-FU	66%	AL-MT-FU	81%
	EO-IP-FU	77%		TT-MT-RE	4%	AL-MT-RE	36%
	EO-IP-RE	24%		TT-FU-RE	63%	AL-FU-RE	79%
	EO-AL-PW	68%		PP-IP-AL	71%	PW-MT-FU	73%
	EO-AL-MT	43%		PP-IP-PW	86%	PW-MT-RE	55%
	EO-AL-FU	81%		PP-IP-MT	62%	PW-FU-RE	72%
	EO-AL-RE	39%		*PP-IP-FU	90%	MT-FU-RE	63%

where: Educational Outreach = EO, Technical Training = TT, Pilot Projects = PP, Incentives Programs = IP, Advocacy and Leadership = AL, Political Will = PW, Maintenance = MT, Funding = FU, Regulations = RE. '*' denotes highest effectiveness within each cohort of strategies. Green denotes synergy, and red denotes conflict.

Policy combinations that were synergistic, meaning they worked together to produce a greater NBS state change than had the policies been implemented in silo, are highlighted

in **Table 15** with green. Policy combinations that were conflicting, meaning they interacted to produce an NBS state vector that was less than (or equal to) that of the corresponding individual policies, are noted in red. For example, strategy PP-RE (pilot projects and local regulations) is a conflicting policy, which resulted in $\Delta S_{PP\text{-}RE}$=47%. However, had pilot projects (ΔS_{PP}=48%) been implemented as a single strategy, we observe a greater change in NBS implementation potential ($\Delta S_{PP}>S_{PP\text{-}RE}$). Such results may be explained by investigating the location of PP and RE within the CLD and assessing how the feedback loops interact. Pilot projects are included in loop **R2** (Funding Loop, w_{R2}=0.54) and **R4** (Advocacy Loop, w_{R4}=0.33), whereas local regulations are impacted by loop **R1** (Maintenance Loop, w_{R1}=0.35) and **R3** (Community Loop, w_{R3}=0.40). The initial strength of the interacting loops for PP (w_{R2+R4}=0.87) is much greater than the initial strength of the interacting RE loops (w_{R1+R3}=0.70). As such, the combination of these policies would not produce a greater end-result after dynamic simulation of the clamped variables, and it could be concluded that implementing the RE policy is not an optimal use of resources.

A similar investigation is used here to explain policy synergy. For example, the combined strategy IP-PW resulted in a state change of $\Delta S_{IP\text{-}PW}$=74%. Had each of these policies been implemented at separate times, and the dynamic interactions not considered, the NBS state would only be 68% (ΔS_{IP}=12%+ΔS_{PW}=56%). In checking the corresponding feedback loops, IP is only included within **R3** (w_{R3}=0.40), which is much weaker than the numerous reinforcing loops impacted by PW ($w_{R1+R2+R3+R4}$=1.62). Even when consider the balancing effects of loop **B1** on political will (w_{B1}= - 0.56), it becomes clear that combing the PW policy with the IP policy results in stronger system dynamic change.

While such manual interpretations of all policy combinations and feedback loops within the system would quickly become burdensome, the proposed CLD+FCM-based scenario approach presented here provides a rapid assessment of how strategies may interact within the system dynamics to produce synergy or conflict. Similar insights may be derived, for example, by ranking the final NBS state vectors (i.e., the ΔS_k values) and noting the occurrence of variables, as shown in **Table 16**. The local funding (FU) variable is present within almost all of the highest-efficiency strategies (i.e., upper quartile). The political will (PW) variable is highly representative within the top-half of strategies, while the only instances of PW within the bottom-half are indeed those combinations that were identified as policy conflicts. In exploring the interaction of associated feedback loops, FU is a component of both the strong balancing loop **B1** and the strong reinforcing loop **R1**, which may have trended the system toward equilibrium had there been no other dynamic forces involved. However, loop **R1** triggers each of the additional reinforcing loops, thereby amplifying total systematic change. This causal logic also explains why pilot projects (PP) and political will (PW) are highly associated with greater NBS impact in the system. Other system variables that interacted with balancing loop **B1**, but which did not have the added reinforcement from loops **R2** and **R3** to counter-act the balancing forces, showcased less favorable outcomes and often policy conflict.

Fig. 23 demonstrates the relative efficiency of management variables by summing the ΔS_k values for each corresponding k. RE, TT, and MT exhibit weak efficiencies when combined with other policy options. An assessment of the associated feedback loops (which are color-coded in **Fig. 24** for improved visualization) demonstrates how these variables are each located on only one feedback loop, thereby triggering less change and

momentum in the overall system trajectory than those variables that are leveraged at the intersection of many overlapping loops.

Table 16. Rank of management strategies and NBS end-state vectors.

Upper Quartile (Q3)		Middle Quartile (Q2)				Lower Quartile (Q1)	
Strategy (k)	Efficacy (S_k), %	Strategy (k)	Efficacy (S_k), %	Strategy (k)	Efficacy (S_k), %	Strategy (k)	Efficacy (S_k), %
PP-IP-FU	90%	EO-IP-PW	74%	TT-PP-AL	61%	EO-TT-AL	42%
PP-AL-FU	88%	IP-PW-MT	74%	PP-AL-MT	61%	TT-PW-RE	42%
IP-AL-FU	88%	IP-PW-RE	74%	PP-IP	60%	EO-AL	41%
PP-IP-PW	86%	PW-FU	73%	PP-AL	60%	TT-AL-MT	40%
PP-PW-FU	85%	EO-PW-FU	73%	PP-AL-RE	58%	TT-AL	39%
PP-FU	84%	TT-PW-FU	73%	EO-PW	56%	AL-MT	39%
EO-PP-FU	84%	PW-MT-FU	73%	TT-PW	56%	EO-AL-RE	39%
TT-PP-FU	84%	PW-FU-RE	72%	PW-MT	56%	TT-AL-RE	37%
PP-MT-FU	84%	PP-IP-AL	71%	EO-TT-PW	56%	AL-MT-RE	36%
IP-PW-FU	84%	AL-PW	68%	EO-PW-MT	56%	AL-RE	35%
PP-FU-RE	82%	EO-AL-PW	68%	TT-PW-MT	56%	EO-IP-MT	27%
AL-FU	81%	TT-AL-PW	68%	PW-RE	55%	EO-TT-IP	24%
EO-AL-FU	81%	AL-PW-MT	68%	EO-IP-AL	55%	EO-IP-RE	24%
TT-AL-FU	81%	EO-TT-FU	67%	EO-PW-RE	55%	EO-IP	21%
IP-AL-PW	81%	EO-MT-FU	67%	PW-MT-RE	55%	TT-IP-MT	20%
AL-MT-FU	81%	AL-PW-RE	67%	EO-PP-MT	54%	TT-IP-RE	19%
AL-PW-FU	80%	EO-FU	66%	EO-TT-PP	53%	TT-IP	18%
PP-AL-PW	79%	TT-FU	66%	TT-IP-AL	53%	IP-MT	18%
AL-FU-RE	79%	MT-FU	66%	IP-AL-MT	53%	IP-MT-RE	18%
EO-IP-FU	77%	TT-MT-FU	66%	EO-PP	52%	IP-RE	16%
TT-IP-FU	77%	EO-PP-IP	64%	IP-AL-RE	52%	EO-TT-MT	14%
IP-MT-FU	77%	TT-IP-PW	64%	PP-MT	51%	EO-MT	13%
IP-FU-RE	77%	EO-PP-AL	63%	TT-PP-MT	51%	EO-TT	11%
PP-PW	76%	EO-FU-RE	63%	TT-PP	50%	EO-MT-RE	10%
IP-FU	76%	TT-FU-RE	63%	IP-AL	50%	EO-TT-RE	9%
EO-PP-PW	76%	MT-FU-RE	63%	EO-PP-RE	50%	EO-RE	8%
TT-PP-PW	76%	FU-RE	62%	TT-PP-RE	48%	TT-MT	7%
PP-PW-MT	76%	TT-PP-IP	62%	PP-MT-RE	48%	TT-MT-RE	4%
PP-PW-RE	75%	PP-IP-MT	62%	PP-RE	47%	TT-RE	3%
IP-PW	74%	PP-IP-RE	62%	EO-AL-MT	43%	MT-RE	2%

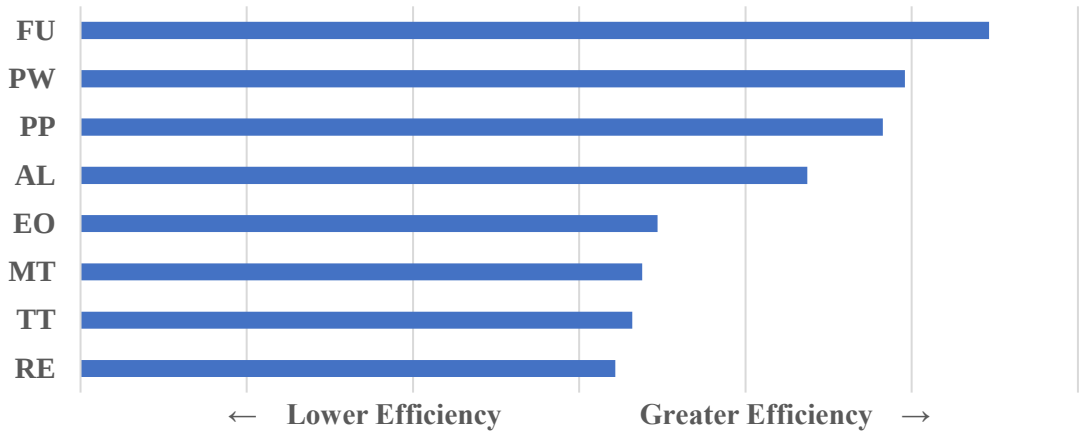

Fig. 23. Relative difference for individual variables toward system efficiency.

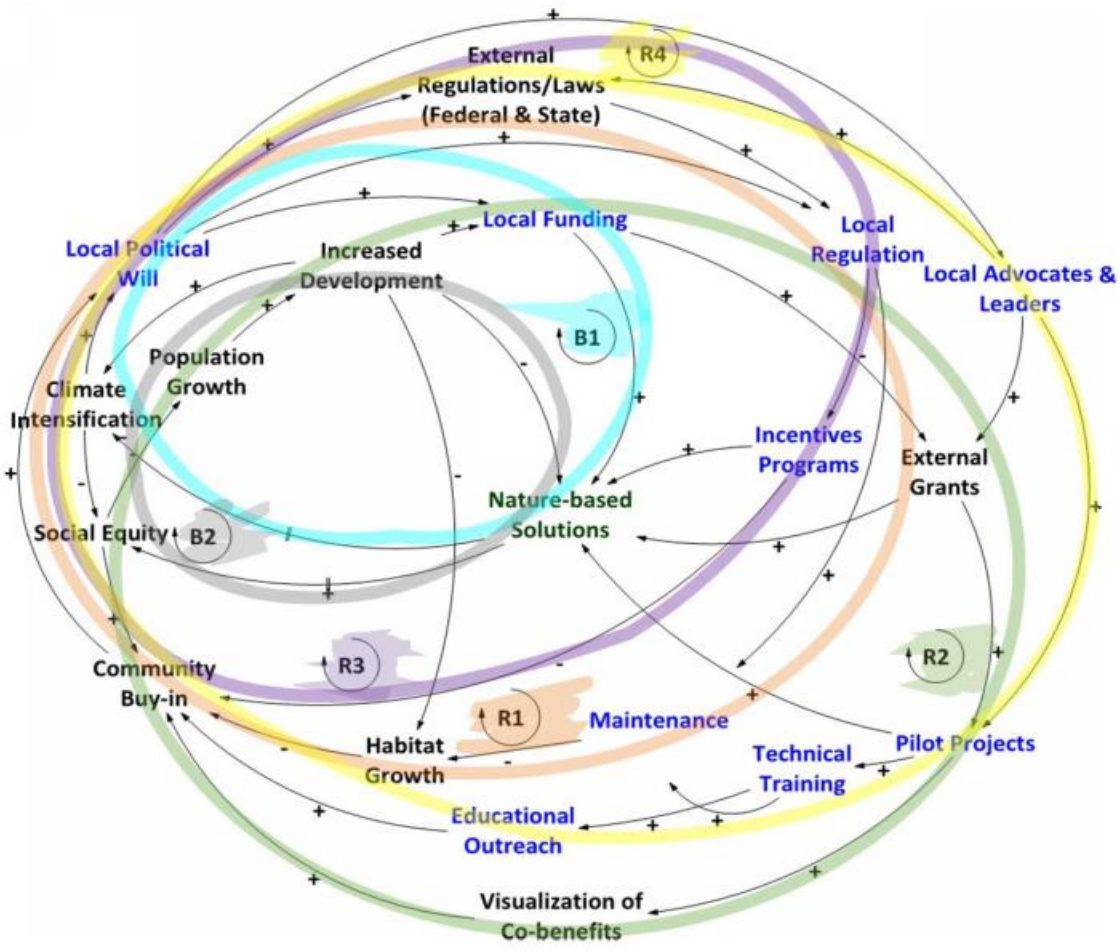

Fig. 24. Color-coded causal diagram with feedback loops.

4.1.4 Discussion of NBS Policy Coherence

Mainstreaming NBSs into urban agendas is a key challenge that must be overcome in order to realize global climate goals (UNEP, 2019), which necessitates understanding the human feedbacks within the system to identify transition variables that, if strengthened, could improve implementation. This research schematized interactions within a complex human-NBS system according to loops and linkages derived from real-world stakeholder input. A holistic approach to systems-thinking provided a means for describing complex behavior and assessing the relative effectiveness of various management strategies in NBS planning.

The initial stages of systems-thinking capture the overall concept of a system from stakeholder knowledge by representing key variables and their interrelationships. An analysis of the resulting feedback loops explains how the system responds to change in a resistant or complementary manner. Policy conflict and synergy stem from these underlying mechanisms that are often difficult to disentangle visually, even at simple scales. Instead, incorrect assessments of interacting feedback loops may lead to the failure of systematic learning and undermine implementation of the most beneficial policies. As systems increase in complexity, computer-based simulations are often necessary to understand how interventions alter the state of the system. Simulation modeling enhances our ability to elicit insights from complex systems by capturing long-term accumulation processes and trajectory shifts. However, SDM-based simulations are typically conducted using data-intensive dynamic models (e.g., SFDs), which are not always feasible when considering human-environmental feedbacks. FCM-based scenario-building is a practical tool for simulating CLD systems by assigning a degree of influence between components, clamping plausible variables, and assessing changes to the goal element (Gray et al., 2014).

This approach assigns meaning to processes that are otherwise difficult to compute by leveraging knowledge embedded within stakeholder experiences and their previous interactions within the system.

A benefit of transposing CLDs into FCMs involves the mathematical foundation of FCMs in graph theory, which provides a computationally-efficient method for rapidly simulating system trajectories. Although coupled CLD-FCM modeling has been demonstrated in the literature (Coletta et al., 2021; Giordano et al., 2020, 2007; Shahvi et al., 2021), it is not commonly used to assess social interactions in policy-making. To transition toward management-oriented research for socio-environmental phenomena, this study encourages the coupling of traditional SDM approaches (e.g., GMB, CLD), which identify the *nature* of the system, with FCM-based scenarios, which simulate the *structure* of the system. By integrating qualitative and semi-quantitative modeling, this approach reveals systemic interactions that would not be clear from CLD or FCM alone, but which also do not require complex modeling with robust datasets. Instead, empirical data for weighted connections may be elicited from the stakeholders at the same time as the GMB session. Such an interactive process transforms elusive systematic barriers into a broad vision of adaptive management opportunities.

4.2 Multifunctional Data System: Hydrology, Ecology, Climate, Society

4.2.1 Results of Suitability Evaluation

4.2.1.1 Characteristic #1: Openness

Openness describes the extent to which geospatial data platforms are attainable by interested users. Open and seamless geospatial technologies are more easily adopted by decision-makers who are not well-versed in GIS data processing. While the traditional suite of Esri desktop-based software is proprietary and requires a paid license subscription for

access, the web version of ArcGIS Online may serve as a platform for sharing GIS data layers through semi-open architecture APIs and geospatial standards. The varying degrees of openness presented by Choi et al. (2016) are assessed (e.g., fully-open, limited-open, permitted-open, or private). Fully-open describes the condition where all datasets and underlying metadata are available to all interested parties, fostering access across both public and private sectors. Limited-open means the complete dataset is not available to the public, but select sub-sets are available in an aggregated manner. Permitted-open describes the condition where datasets are available but are subject to additional limitations and permissions, according to the hosting agency's conditions of use (Choi et al., 2016). Private datasets are only available to authorized users within the hosting agency's internal organization. In crafting the NBS-Geo web mapping application, various levels of openness were encountered within the Living Atlas repository.

Since the Living Atlas uses a combination of publicly authoritative and private vendor-based users for hosting created content, the resulting GIS web app was a mixture of fully-open, limited-open, permitted-open, and private datasets. To facilitate public access for the web app without requiring prior ArcGIS organizational account credentials, some fully-private datasets that may have been otherwise included in the NBS-Geo curated content were strategically removed from the final web version (i.e., NatureServe's biodiversity maps). Organizational costs associated with gathering, managing, and hosting geospatial data may limit its fully-open accessibility. Even so, this research encourages additional ongoing development to facilitate the use of fully-open datasets across disparate epistemologies. Particularly within the United States, there is an increasing urge toward geospatial data transparency, in which information produced using public expenditures

(i.e., tax-payer money) should be made fully-open and freely available to improve public involvement and policy-making (Vitolo et al., 2015).

While this approach of pre-authorizing the ArcGIS Online organizational credentials provided a functional solution for public dissemination of NBS-Geo, several limitations associated with the semi-open nature of the Esri Living Atlas are noted. For example, the user must still supply organizational credentials in order to download and subsequently perform spatial analyses on the underlying data. (The pre-authorization technique imposed for public access only provides visualization capabilities and does not allow data extraction without a licensed Esri account.) This requirement for association with an organizational account is one of the main hindrances of widespread usage of the Living Atlas, as evidenced in its limited representation within the literature. Instead of necessitating a lengthy process of pre-authorization through personal credentials, an ongoing transition toward fully-open geospatial data repositories is essential, especially considering how much of the underlying information contained in these layers stemmed from open-access, governmental datasets. The issue regarding geospatial data availability is not a matter of cost, as many governmental organizations host their GIS data online for free (i.e., FEMA, USGS, NOAA). Rather, we lack strategic selection and amalgamation of these many disparate datasets, each hosted in a unique format and location across the internet, into a readily deployable application that may be quickly used by technical and non-technical audiences for informed decision-making.

4.2.1.2 Characteristic #2: Spatial Analysis Functionality

Spatial analysis functionality within webGIS refers to the integration of data and people according to geospatial relationships disseminated through a web-based user interface

(Veenendaal et al., 2017). Location is used as a common denominator to link the user's visualization inquiry with a select subset array from large-scale datasets. While such functionality provides rapid data access for browsing, users often necessitate performing additional analysis upon the curated subsets to understand local scenarios. Spatial analysis of correlated datasets describes the usage of functional properties (i.e., geospatial location and/or attributes) to transform data into new formats and to impose modifications toward a specific goal. For example, in the hydrological sciences, spatial analysis is commonly performed to transform landscape datasets, such as terrain elevation, soils, and land use, into standardized formats, which are then further merged, processed, and assessed to derive representative model elements and describe the flow of water throughout the watershed.

In the NBS-Geo web app, much of the data accessed from the Living Atlas repository was found to be analysis-ready, both in terms of webGIS and local processing. The primary spatial analysis limitations associated with this web app involved the difficulties encountered with extracting data subsets to a local computer, which is necessary for performing robust geospatial operations. High-resolution watershed modelling was thereby limited by the need for the user to obtain organizational credentials for proper data downloading and also the need to possess costly Esri license extensions on the local computer (i.e., Spatial Analyst, 3D Analyst; See Castro and Maidment (2020) for an example of standard hydrological terrain processing steps within a GIS environment utilizing such extensions.) Furthermore, several out-of-the-box widgets were implemented in the NBS-Geo web application, which were intended by Esri to provide value-added spatial functionalities within a web application without necessitating complex coding skills by the developer (Esri, 2017). While in theory, pre-built widgets would aid facilitation of

cloud-based GIS data and user-friendly web applications, practical usage of such tools were found to be hindered by the underlying geospatial limitations of the Esri web app suite.

For example, the “swipe widget” used in NBS-Geo was not intuitive in terms of how to achieve proper data overlays and transparency symbologies to showcase overlapping land use classifications. When using this widget, the user is required to manually turn on all land use layers while turning off all other layers for proper visualization. The “screening widget”, used here to showcase the CDC’s SVI vulnerability themes within the user’s viewport, did not provide the capability to modify the legend nomenclature for clarity and resulted in small text that was sometimes hidden from view. To mitigate user understanding of this widget information, a text link was included within the widget for the CDC’s SVI data documentation. A demonstration video was added to the tool’s homepage to help clarify how these widgets may be used. However, further improvements regarding ready-to-use webGIS widgets would facilitate spatial analysis functionality for the end-users without necessitating additional or ongoing training by the developers. Additional widgets created by Esri for robust spatial investigations were investigated, such as user-defined hotspot mapping and cloud data extraction, but various limitations in the types of data that could be incorporated into such widgets hindered practical usage. Only data layers that had been identified by the hosting agency as fully-open and extractable could be used in several of the added-value Esri widgets, thereby limiting robust application within a comprehensive collection of datasets, each containing varying levels of openness.

Spatial functionality also includes the management of GIS datasets and value-added tools for long-term user functionality. During the course of this tool development, several datasets within the Esri Living Atlas had been depreciated by the hosting agencies and

updated with newer data. This necessitated manual re-linking of the underlying data REST URLs within the NBS-Geo web map in order to update the datasets on visualization portal. Dataset depreciation was typically notified by a user of the NBS-Geo tool and not immediately informed by the developers of the dataset or the hosting repository. Identification of new datasets that may be applicable for holistic NBS planning also required manual searching of the Living Atlas repository on a periodic basis. This brings up the question: *Whose responsibility is such data management, maintenance, and curation when the underling information is derived from a variety of sources?* Data depreciation is likely to occur at-scale as new data is derived by the GIS community, which necessitates improved best management practices regarding large-scale data hosting repositories (e.g., automated user notification of depreciation, automated linkage to latest datasets within web applications) for optimal use in transdisciplinary research frameworks.

4.2.1.3 Characteristic #3: Scalability

As the cloud web mapping era has increased, the scalability of mass information has become a key observed benefit (Veenendaal et al., 2017). Here, scaling refers to the ability of the two-way feedbacks between data and end-users to occur at cascading levels of computing power, size of data, and geographical area of interest. The cloud computing within ArcGIS Online, which uses a software-as-a-service platform, fosters scalable computing and storage using immense technological resources to iterate data queries in rapid time. Several of the datasets referenced in NBS-Geo were provided in real-time (i.e., stream gauges, air pollution monitors, wind data), which necessitates instant context and dynamic data display from the local- to the regional-, and even the national-scale. The cloud-based computing technologies then leverage resources from disparate servers to scale up user queries within the web mapping applications and perform geospatial

operations for real-time situational awareness (Dangermond, 2019). Cloud-based datasets can contain a significant number of pixels for data visualization, and limits to the scale in which the user may view the datasets is often incorporated into the data symbology attributes for enhanced functionality over the internet. For example, the building footprints layer hosted in NBS-Geo was automatically set for a visibility range of 1:10,000 square meters by the hosting agency, meaning the dataset will not display until the user is zoomed in to a map area of 10,000 square meters or less (approximately street- or neighborhood-scale). The benefits of such scale-dependent data mapping are enhanced organization among potentially convoluted sets of data and computational performance improvements; however, scale-dependent rendering may also limit data visualization at larger scales, which are important for regional planning. Through the exercise of building NBS-Geo from the Living Atlas, there exists a robust opportunity to scale data using such a framework from local to regional areas. This capability promotes place-based risk assessments according to community priorities across institutional boundaries.

4.2.1.4 Characteristic #4: Geospatial Standards

Another important component of web mapping applications is adherence to an agreed-upon set of geospatial standards and specifications. One of the most common sets of geospatial standards was developed by the Open Geospatial Consortium (OGC), which provides ease of accessibility, interoperability, and combination with other software suites (M. Zhang et al., 2020). Another set of fundamental standards was derived from the International Organization for Standardization (ISO) for describing inherent data construction, quality management approaches, and workflow implementation (Veenendaal et al., 2017). Within the Living Atlas, hosted datasets are intended to be well-documented according to OGC or ISO geospatial standards. However, during development of NBS-

Geo, there existed many instances where the hosted datasets did not contain adequate metadata for fully understanding how the datasets were created. In attempting to better understand the scientific basis for several datasets, manual contact of the hosting agencies was necessary to obtain pertinent background documentation. There also existed many instances where the nomenclature for the geospatial attributes used within a hosted data layer was not intuitive, which required additional searching online for core documentation and legend descriptions (i.e. CDC (2016), Jin et al. (2019)). Such information, which is necessary for data dependability and reproduction capability, should be easily accessible directly within the geospatial metadata descriptions.

Due to the manner in which the Esri Living Atlas data is compiled by contributions from a plethora of user-types (i.e., commercial, academic, general GIS users, governmental), and not all datasets have been vetted as authoritative, we necessitate further efforts to comprehensively document the underlying datasets involved in holistic NBS planning and research. While this study benefited from the use of a comprehensive web-based geospatial repository for amalgamating an interdisciplinary traffic of ideas and cross-domain datasets, the end-users will likely stem from a siloed domain of understanding and will therefore require easy-to-understand and easy-to-find metadata descriptions for digesting and adequately using the information available within GIS web applications.

4.2.2 Discussion of NBS-Geo

Historically, spatially-distributed social data sets have been a significant missing link in forming a cohesive spatial framework for complex, overlapping multifunctionalities of human-earth-water systems (Cumming, 2011). Latest improvements in geospatial technologies have strengthened our ability to access social datasets as a function of space toward amalgamating social phenomena with physical properties. NBS-Geo is a

representative of that potential by providing systematic access to multidisciplinary information regarding the full scope of NBS functions. This study presents the overall framework behind NBS-Geo to link disparate systems and foster identification of unique feedbacks between social and hydro-environmental patterns. As sustainability emphasizes the compounded properties of societal and environmental importance, NBS-Geo incorporates overlapping geospatial datasets encompassing quality of life metrics, environmental degradation, and social vulnerability. When addressing properties of resilience, both baseline and future conditions must be considered. NBS-Geo amalgamates the long-term and acute stressors of climate change, immediate weather conditions, and land use changes resulting from projected urbanization trends toward a holistic framework for planning compound climate solutions.

One of the novelties of the NBS-Geo framework includes the curated collection of web-based datasets that reflects the current state-of-the-art in NBS efficacy across a variety of distinct, albeit complementary, domains. By combining open-source and proprietary geospatial technologies for data generation, management, sharing, and visualization, NBS-Geo improves research and planning that links disparate systems to increase our understanding of complex hydro-socio-environmental connections. By providing a framework that connects users with comprehensive NBS data at a high-level planning stage, NBS-Geo is customizable to any geographic region (within the limitations of the datasets) and may be used to elucidate generalizable understandings regarding engineered NBS technology in urban environments. The practical implications of this research will enhance the user-friendliness of NBS spatial planning in a flexible manner while merging well-established hydrological considerations with a vast spectrum of NBS co-benefits.

Moreover, GIS licensures, access credentials, and data maintenance presents an additional layer of challenges that must be overcome for full embracing of GIS web app technologies in cross disciplinary research and planning. Integrated data resources that enable robust data discovery and usage toward derived wisdom must contain the primary geospatial attributes discussed in this study, namely: 1) Openness, 2) Spatial Analysis Functionality, 3) Scalability, and 4) Geospatial Standards. This study elicits areas of strength and further research opportunities in the field of GIS toward achieving such goals. Future best-practices for interdisciplinary data mash-ups are highlighted by assessing the current suite of cloud-based GIS datasets accessible during this study and assessing their fitness-of-use for actionable decision-making. As such, this research highlights the importance of robust data technologies and management schemes to overcome challenges of interdisciplinary data science in the era of the Anthropocene, where human interaction and accessibility of information are just as important as the datasets themselves.

4.3 Equity-based Optimization for NBS Planning

4.3.1 Hydro-environmental Pareto Front Curve

The GreenPlan-IT optimization tool for the WOB watershed converged after 100 generations, each with approximately 250 population values (i.e., series) 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. 25**. 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. 25** 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. 3.3.4**, the 5-YR storm event with $1,000M NBS expenditure was chosen for further analysis. Here, 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 (reference **Fig. 28a-b**), 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.

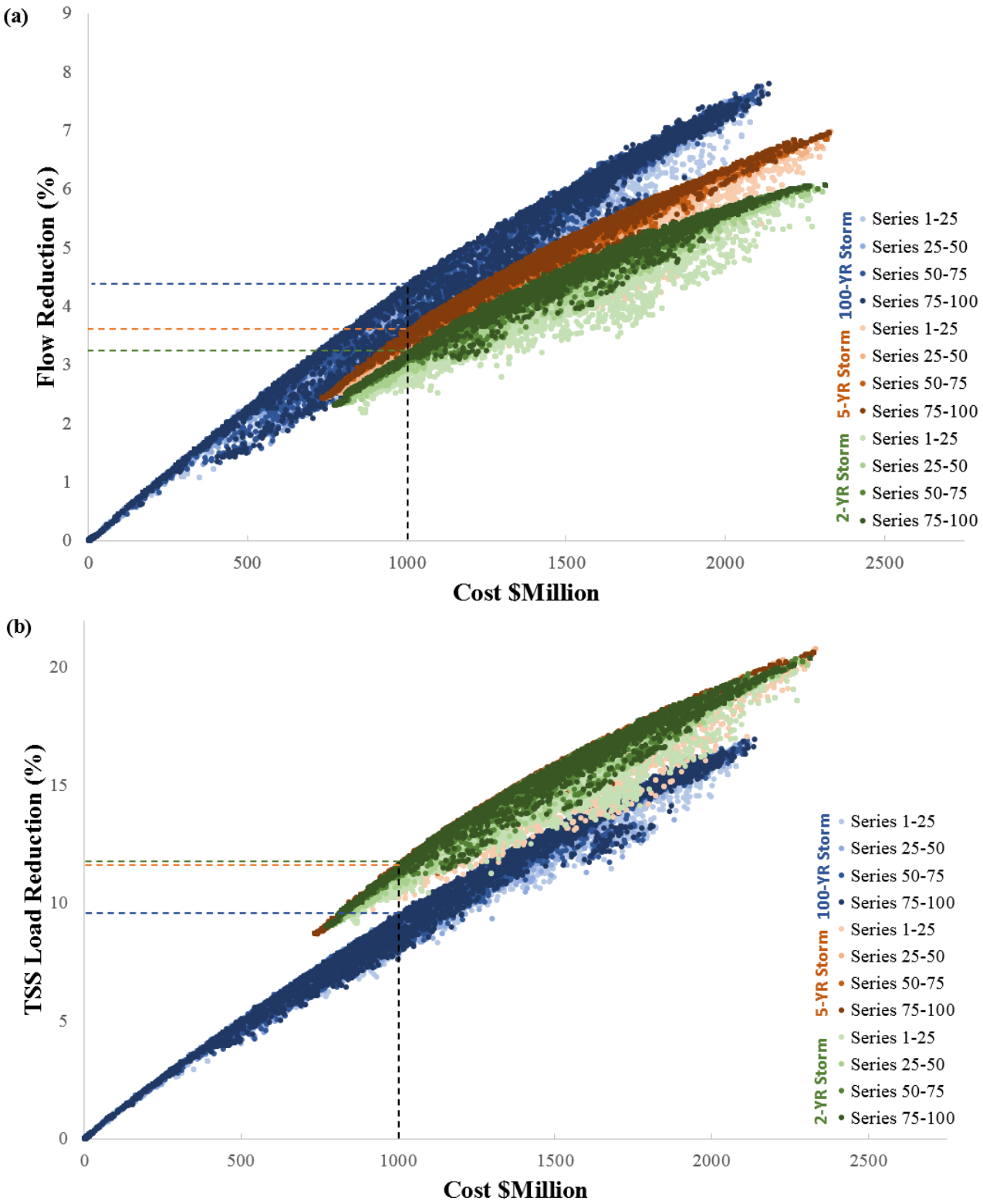

Fig. 25. GreenPlan-IT output for WOB: **(a)** flow reduction as a function of cost-efficiency; **(b)** pollutant load reduction as a function of cost-efficiency for the 5-YR storm.

4.3.2 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. 26**, 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. 26b** reveals poor allocation fairness corresponding to spatial distribution of neighborhood deprivation.

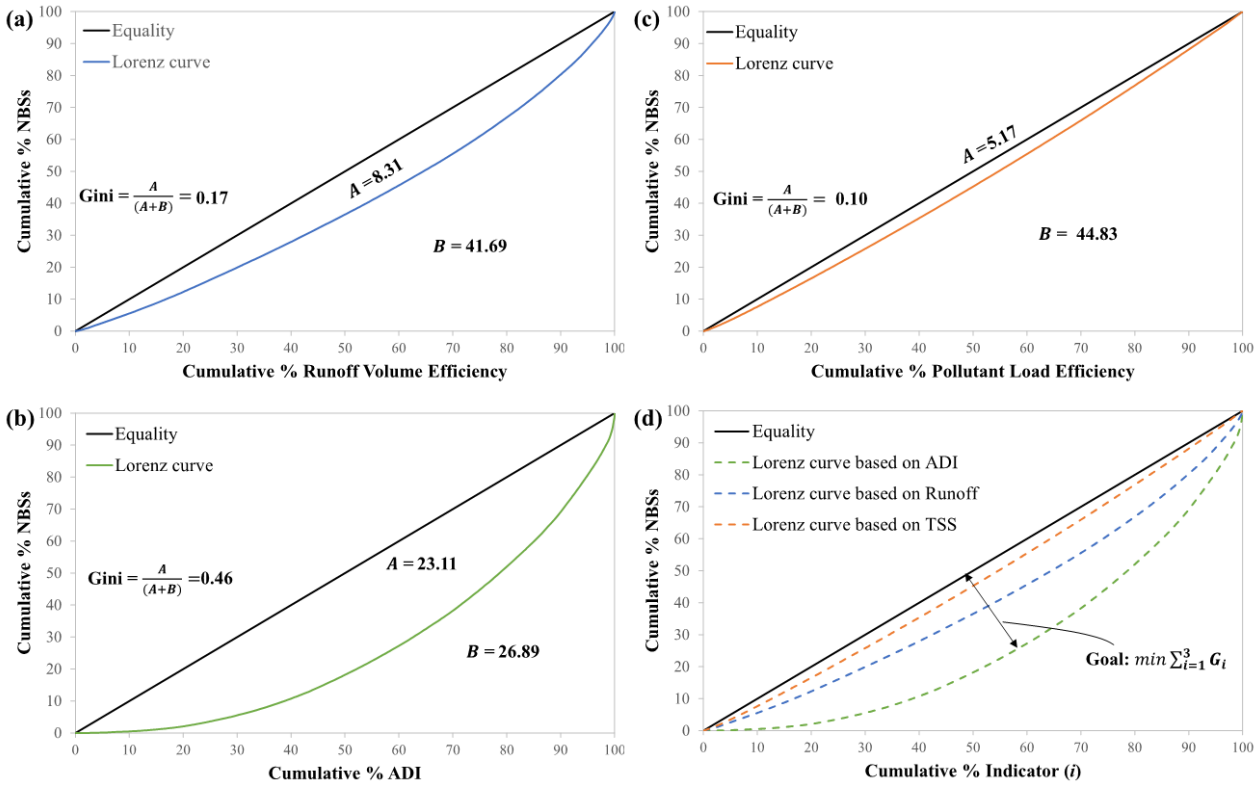

Fig. 26. Gini coefficients based on **(a)** runoff volume efficiency, **(b)** pollutant load efficiency, **(c)** Area Deprivation Index, and **(d)** cumulative indicators for the 5-YR storm.

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. 27** and summarized in **Table 17**, 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. 27** 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, 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 (**Fig. 27**), 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, providing a transparent tool of the average impact fractions for multi-objective planning (Lee, 1997).

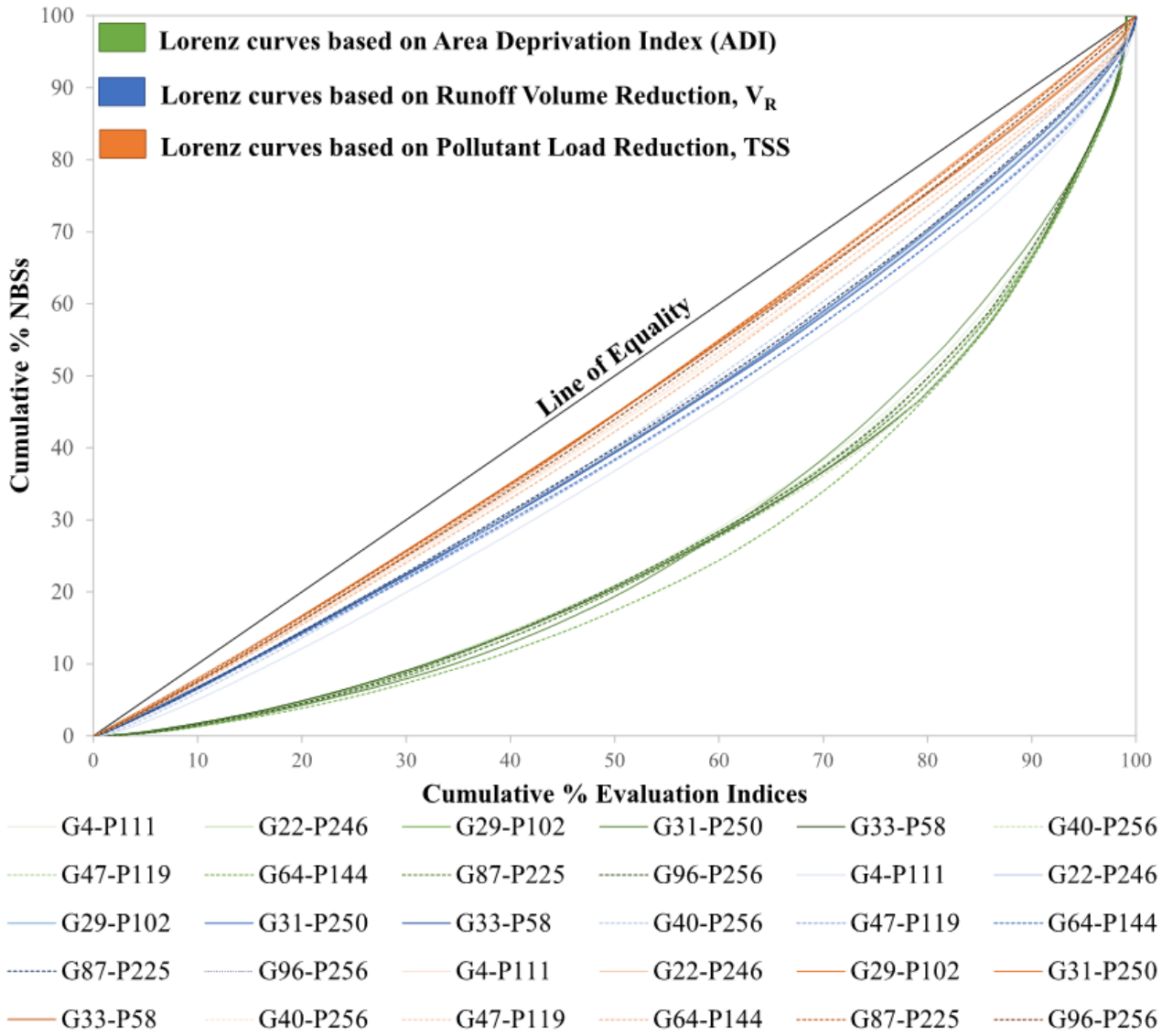

Fig. 27. Series of Lorenz curves for select 5-YR, ~$1,000M optimization models.

Table 17. Multi-objective Gini coefficients for 5-YR storm series.

Gen Pop	G4 P111	G22 P246	G29 P102	G31 P250	G33 P58	G40 P256	G47 P119	G64 P144	G87 P225	G96 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
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. 28**, 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. 28d** 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 18**, both allocation scenarios produced 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. 29**, 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. 29** reveal 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.

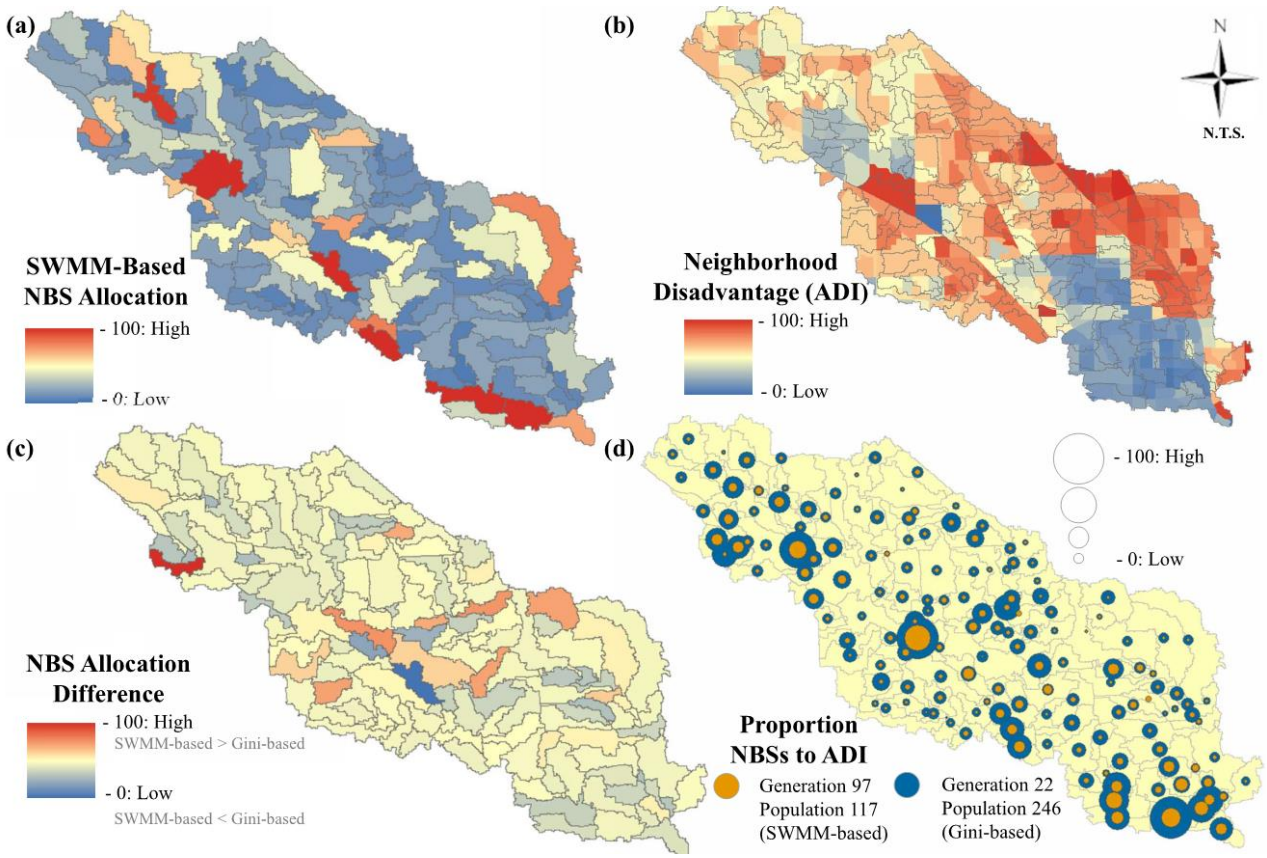

Fig. 28. Spatial distribution for the 5-YR storm per **(a)** SWMM-based optimization, **(b)** ADI deprivation, **(c)** difference between SWMM-based and Gini-based optimization, and **(d)** weighted proportion of NBSs to ADI deprivation.

Table 18. Comparison of 5-YR, SWMM-based versus Gini-based optimization 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%

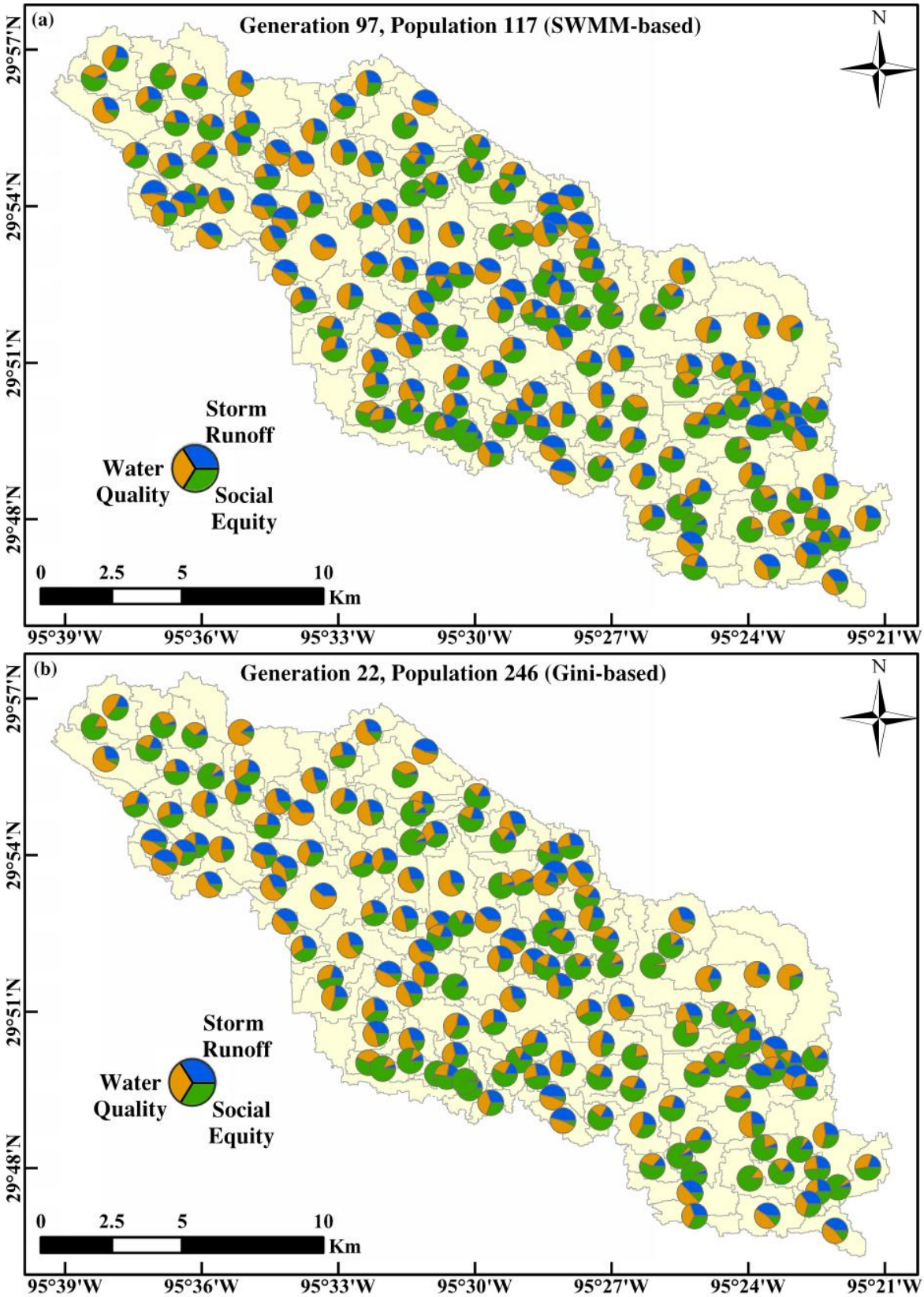

Fig. 29. Proportional representation of evaluation indicator efficiency for **(a)** SWMM-based optimization model, and **(b)** Gini-based optimization model.

4.3.3 Discussion of Multi-objective Gini

By solely relying on hydro-environmental modeling, the relative benefits addressed by NBS solutions are limited and are not able to be optimized according to unique exposures of socio-economic and health-related conditions. The framework presented here converts hydro-environmental risk and social disparity into a common unit for comparison to adequately capture variation across spatial domains. The Gini index and Lorenz curve are presented as an alternative fundamental approach for optimal NBS planning.

This study demonstrates 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 investigates how social equity and watershed dynamics propagate throughout the NBS system, which is fundamental to planning for an equitable environment. This study harmonizes multi-indicator planning by facilitating an explicit integration of social determinants within the framework of natural-planning using data-driven science. Improving resiliency begins with valuing the entangled nature of social well-being and water dynamics. The framework demonstrated optimizes NBS strategies by assessing unique scenarios and minimizing the Gini coefficient across three disparate, but equally important, human-water domains of NBS systems using existing tools and methods in a novel way. As we continue to have increased access to heterogenous datasets, the spatial Gini coefficient maximizes our understanding of spatial risks and benefits to answer challenging questions associated with multi-functional planning.

The practical implications of this research will enhance the user-friendliness of NBS spatial planning in a flexible manner while merging well-established hydrological methodologies with NBS social functionalities (Kuller et al., 2017). When we are better able to select the optimal location of NBSs at a large-scale, the specific typologies and

precise placement may be analyzed using the numerous platforms that currently operate through small-scale physical modeling. To date, there has been very little research on NBS optimization at the catchment-scale and even less progress in combining numerical modeling with comprehensive social benefits and human impacts. This study successfully integrates various types of NBS co-benefits into one inter-related framework that combines stormwater abatement, pollutant load modeling, cost-efficiency, and social equity-based decision-making for robust spatial optimization of NBS systems at the planning scale.

5. CONCLUSION

Renewed global mandates have encouraged a proliferation of NBSs for addressing overlapping benefits of hydrological impact, social conditions (e.g., mental and physical health, sense of well-being, vulnerability), and environmental health. According to UNEP (2019), widespread use of NBSs could reduce global greenhouse gasses by up to one-third the total emissions required to meet the Paris Climate Agreement. Robust investment in NBSs will help to offset the negative financial consequences of climate change while providing new jobs, reducing poverty, and supporting the UN Sustainable Development Goals through improved livelihoods, food security, and ecosystem restoration. NBSs are an essential component toward the overall global effort of establishing resilient and sustainable societies by promoting harmony between people and nature in a cost-effective manner. Specifically, NBSs are important for conserving and improving terrestrial ecosystems, freshwater resources, sustainable agriculture, and just transitions from rural to urban migration (UN Environment Programme, 2019). However, the decision to implement nature-based solutions in an optimal manner is posed with challenges that transpose complex interactions between human behavior and physical watershed phenomena. In the burgeoning era of Anthropogenic science, NBSs serve as a prime foundation for exploring linkages between climate change, rapid urban development, quality of life goals, and a scarcity of resources for addressing hydro-meteorological challenges. NBSs serve numerous cross-cutting themes by utilizing nature to address climate and environmental adversaries while also promoting the human capacity to adapt to these adverse impacts. To amalgamate such inter-woven goals, decision-makers seek the ability to identify priority planning areas that guide equitable investment for multi-

dimensional benefits (Marchese et al., 2018). To-date, NBS planning paradigms have faced numerous challenges regarding adequate spatial distribution of social and physical health characteristics due to a lack of comprehensive datasets, equity-based planning frameworks, and socio-institutional governance strategies. We therefore necessitate enhanced approaches to integrate science with policy toward the informed use of NBSs. This study explored the transdisciplinary complexities of NBSs through the lens of socio-hydrology and proposed several novel approaches for incorporating human characteristics within large-scale NBS planning.

5.1 Advancing Data-driven Systems

A novel NSDI was derived that uses real-time, dynamic mapping to promote information sharing and access from various governmental, non-profit, and private agencies by binding loose geospatial datasets across the NBS paradigm into a coupled information network. A comprehensive spatial framework for NBS characteristics has been hitherto missing within the literature and is necessary for addressing the overlapping challenges of global climate change and urban development. When considering how to unlock the full potential of NBSs, a strong spatial component of NBS mitigation metrics is essential for informed research and decision-making. However, due to the disparate domains associated with NBS systems, a large number of geospatial datasets with varying spatial resolutions is necessary, thereby increasing the complexity of sound and actionable data management. Traditionally, spatial data queries for generating multidisciplinary maps are run against many thousand GIS features, which pose challenges with data access for users outside of the hosting organization. Therefore, a robust metadata server and searching tool becomes critical for simplifying this process to support applications that extend beyond the data's original intent. We currently invest billions of dollars to automate and

integrate geospatial information for focused use, yet this has not yet been done for NBSs in a manner that is publicly-accessible. Toward this goal, a comprehensive NSDI will allow us to better understand the spatial elements associated with NBS complexity and support widespread data collection, access, and decision-making strategies.

An NSDI system is a geospatial framework that connects users with multiple sources of spatial data to enhance understanding of the physical and social environment. NSDIs consist of conglomerate datasets with corresponding documentation (metadata) for accessing, discovering, visualizing, and evaluating large amounts of information. NSDIs enable trans-institutional GIS data management by distributing the information costs among many users, thereby reducing redundancy in data gathering and creation, further allowing data collected for a specific goal to be used by the broader community in a generalized format. At the core of NSDIs is the concept of collaborative research across institutions and organizations for the public good, whereby costs and benefits of widespread data management are shared communally. Through interoperability, users become embedded within the system at a semantic level and act as agents to decode vast amounts of information and elicit value-added insights (Working Group on Planning (GTplan), 2013). To be successful, NSDI systems must be interoperable, meaning the data is accessible irrespective of the user's platform, physical location, or organizational affiliation, while providing robust decision-making and coordination capabilities through strategically harmonized and curated datasets. As such, this study extended beyond providing a useful NSDI for NBS planning by also performing a detailed assessment of the current geospatial capabilities available for advanced NSDI interoperability. Specifically, the geospatial framework presented here was measured against the primary components of

a reliable NSDI (namely, openness, standardization, scalability, and spatial analysis) to ensure seamless operation of end-use searches across the web interface.

The proposed NSDI application, called NBS-Geo, combined long-term and acute stressors of climate change, land-use, urbanization trends, quality of life metrics, ecological health, and hydrological risk toward a holistic, risk-based framework. The four domains integrated within NBS-Geo (social, hydrologic, environmental, and ecological) comprise an amalgamation of biotic and abiotic components, which must be viewed as a system of interacting and unified goals that, when linked collectively, describe the overall system (Stokols et al., 2013). By approaching the system as a linkage of spatial properties, this study highlights the important synergies associated with multiple human-water objectives, thereby reducing the potential for systemic underperformance (sustainability) or deformation in light of outside stressors (resilience) (Marchese et al., 2018). By amalgamating candidate NBS datasets into one platform, the proposed NSDI provided the critical function of data interoperability across organizations, which is necessary to generate useful insight from disparate domains as we attempt to scale-up compounded climate solutions. Moreover, by integrating various epistemologies, this novel analytical approach serves as a representation of complex landscape functionality and their interactions for improved systems science. The importance of location, connectivity, and social context may now be revealed according to the spatial variation of socio-hydro-enviro-ecological patterns and processes at cascading scales. Given the rapid increase in high-resolution, reliable, and transdisciplinary global datasets as a function of space, NBS-Geo serves as a framework for bridging the gap between end-user and data contributor as we work collectively toward enhanced Global Spatial Data Infrastructure (GSDI) systems

(Working Group on Planning (GTplan), 2013). The detailed assessment of NSDI metrics within the NBS-Geo framework reveals the current state of GIS science and highlights further efforts necessary to create consistent and useful web-based geospatial data servers.

5.2 Balancing Economic, Social, and Hydro-environmental Needs

In addition to a lack of spatially-distributed datasets linking the human and physical properties of NBSs, widespread adoption is often further challenged by social and institutional constructs that are not well-understood. A key issue in designing effective NBS policies includes the inability to examine a range of complex system properties and to describe alternative management strategies. Policy-making with limited resources and external human influence requires an understanding of social dynamics within planning frameworks, as a shift in one system variable could trigger self-regulating and/or divergent outcomes elsewhere (Frantzeskaki, McPhearson, Collier, et al., 2019). As such, proper co-development of NBS plans should include expert input from scientists, practitioners, and local community constituents for a weaving together of pertinent insights across diverse disciplines. Toward this goal, a novel framework was presented and demonstrated that applies a series of soft-systems approaches to elicit the complex interactions between the physical processes served by NBSs and their human-directed management opportunities.

Flows of information throughout the human-water cycle are often transformed by belief systems embedded within stakeholder cognition. This study employed a novel semi-quantitative scenario-based assessment, coupled with causal loop logic, to identify and better understand such flows of information amongst a plethora of decision-making options. Typically, sole reliance upon scenario-based modeling obscures the feedback loop logic embedded within the system. Conversely, causal loop diagrams alone may quickly become convoluted, which are difficult to decipher from human visualization when we

encounter double and triple loop influences. By combining both loop analysis and scenario-based modeling within one framework, we are better able to *identify* areas of policy effectiveness while also *explaining* the emergence of synergies and trade-offs according to causal loop logic. The community-led application highlighted stakeholder collaboration as a means for balancing complex governmental structures when working with multiple agencies. Unique synergies and conflicts between potential NBS management strategies were revealed and described as function of policy coherence. Demonstrated by the WOB case study, unexpected system feedbacks were discovered that resulted from complex causal influences across the social and hydrological domains (e.g., the influence of climate change, flood memory, advocacy, political will, and benefit visualization). As such, several major barriers associated with NBS implementation, which had hitherto been studied as a series of siloed case studies, were revealed holistically by combining the strengths of system dynamics with cognitive mapping.

The framework demonstrated here promotes a deeper awareness of dynamic feedbacks in the initial planning of complex systems and denotes the elucidation of policy coherence as a primary goal for holistic systems-thinking. By amalgamating cognitive modeling with causal loop logic, we extend beyond identifying the nature of the system to also elucidate the behavior and structure of the system amidst complex policy-driven interactions. Such a framework is applicable to a variety of complex systems with overlapping socio-hydro-environmental processes that are influenced by political decision-making across institutional scales. This study highlights how identifying the nature of the system must be supplemented by also identifying the social context within which the system is embedded, demonstrated here through a novel representation of NBS planning as a complex human-

environmental system. This integrative approach enriches the theoretical merging of systems-thinking epistemology (i.e., embedding human cognition within the system), with ontology (i.e., using the underling structure of the system to elicit insights). In summary, this novel framework demonstrates how we may approach human-earth problems as a web of interlinked connections with weighted interdependencies through the lens of systems-thinking, thereby providing a mechanism based on cognitive reality to better understand management actions within a rapidly changing world.

5.3 Overlapping Co-benefits & Decision-making

This improved understanding of NBS decision-making and geospatial properties may be leveraged to inform an explicit representation of social equity within holistic planning frameworks. As described in **Section 2.2**, NBS systems have been shown to improve social conditions by providing enhanced metrics of mental well-being, physical health, aesthetic appeal, recreational opportunity, and general livelihood. A right first step toward fully encompassing such NBS multi-functionalities is to represent disparate phenomena (i.e., stormwater runoff, water quality, and social well-being) as unique functions of space and to quantify their tradeoffs through the lens of overlapping disciplines. However, traditional NBS optimization schemes have prioritized 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 & Chui, 2018). By relying primarily on hydro-environmental optimization, existing NBS planning frameworks do not fully espouse human characteristics (e.g., socio-economics, health metrics) in a manner that impacts the overall communal benefits able to be realized by the system. In other words, the unique spatial exposures of social deprivation that could benefit from NBSs are not well-captured in current optimization models. Instead, general estimates of social

vulnerability are incorporated within preliminary planning stages through coarse visualization of geospatial hotspots and are not embedded directly within high-resolution planning schemes. A recent state-of-the-art review described how consideration of social 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). 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 & Wu, 2020).

This study presented and demonstrated a novel framework to integrate hydro-environmental modeling, economic efficiency, and social deprivation using a dimensionless Gini coefficient, which is intended to spur the positive connection of social and physical influences within robust NBS planning. Hydro-environmental risk and social disparity were combined within a common measurement unit to capture variation across spatial domains and to optimize fair distribution across the study area. Advances in neighborhood-scale datasets for measuring social deprivation were leveraged to improve fundamental, multi-objective planning in human-water systems. A case study in the White Oak Bayou watershed in Houston, Texas, USA was used to demonstrate how the optimal spatial allocation of NBSs is location-dependent with varying tradeoffs across overlapping goals (e.g., stormwater runoff mitigation, water quality abatement, economic efficiency, and equity-based allocation). Current stormwater management within the study area 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, such as ability to recover from a storm or the reinforcing impacts of hydro-environmental hazards on socio-economics.

This study is the first known attempt to incorporate NBS synergies and tradeoffs between hydrology, social depravation, environmental quality, and cost efficiency into a single framework using robust, data-driven optimization. In doing so, this study re-shapes the NBS planning process by transcending beyond flood risk to also include equal distribution of social benefits as an explicit policy-making mechanism. The composite Gini coefficient demonstrated how water resources planning may be addressed as a holistic system of human-water phenomena to minimize tradeoffs across disparate domains. Social justice was improved in the Gini-based optimization scheme, while the overall costs and hydro-environmental efficiencies were similar to the optimal NBS scenario based solely on watershed modeling. By constructing model with such inter-disciplinary elements, this framework strengthens the foundation for novel research regarding the complex associations between social patterns and watershed physiological characteristics. As such, water resources planning may be improved by more thoroughly balancing economic, social, and hydro-environmental needs to ensure equitable allocation of climate solutions.

5.4 Systems-based Approach to NBS Planning and Management

In the era of the Anthropocene, change is occurring rapidly, and we must better understand complex socio-hydrological systems to address variability in climate and human patterns. Instead of attempting to super-impose human dynamics on the result of physical models, or as a pre-existing boundary condition, we must transition toward coupled modeling frameworks that integrate human characteristics as a stimulus that interacts with the environment (Bouziotas & Ertsen, 2017). We can no longer study watershed systems as fixed within a vacuum of ideal boundary conditions and static forces.

In order to prepare for the rapidly changing world, we must understand and account for the multifunctional 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. In doing so, we begin to identify important feedbacks and transitional variables that, if strengthened, could improve the adaptability of the overall system regarding climate concerns, societal injustices, political forces, and other complex challenges through a socio-technocratic lens (Penny & Goddard, 2018; Schlüter & Pahl-Wostl, 2007).

In this light, strategic NBS planning requires real-world empirical datasets (e.g., human behavior, geospatial 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). This study revealed how transdisciplinary methods of analysis can help decision-makers, from community participants to regional decision-makers, improve NBS planning in light of overlapping themes. When we are better able to connect the dots between social constructs, environmental processes, and the hydrological cycle, which are all dynamic adaptations that transform and co-evolve amongst one another, we can establish patterns within the seemingly chaotic network of NBS sub-processes. From there, we can better understand how the system will respond to changes,

such as intensified climate change or rapid urbanization, and how our decisions at present might improve or undermine the overarching system stability.

This research transitioned beyond the standard focus of NBS landscape characteristics to investigate the complex associations relating social patterns and hydro-environmental efficacy. This study integrated methods from diverse fields (e.g., geomatics, hydrology, environmental science, social science, multi-objective optimization, systems-thinking, decision science) to strengthen actionable NBS frameworks and to explore the interplay between NBS design, policy-making, and watershed organization. In light of ongoing climate change and urban development, this study amalgamated robust hydrologic modeling with novel theories regarding human behavior and equitable planning to strengthen NBS adoption and further support vital ecosystem services, social livelihoods, and hydro-meteorological risk reduction through strategic use of greenspaces within the built environment.

REFERENCES

Addala, A., Auzanneau, M., Miller, K., Maier, W., Foster, N., Kapellen, T., Walker, A., Rosenbauer, J., Maahs, D. M., & Holl, R. W. (2021). "A decade of disparities in diabetes technology use and HBA1c in pediatric type 1 diabetes: A transatlantic comparison." *Diabetes Care*, 44(1). https://doi.org/10.2337/dc20-0257.

Agrawal, S., & Gupta, R. D. (2017). "Web GIS and its architecture: A review." *Arabian Journal of Geosciences*, 10(23). https://doi.org/10.1007/s12517-017-3296-2.

Agyepong, I. A., Kodua, A., Adjei, S., & Adam, T. (2012). "When solutions of yesterday become problems of today: Crisis-ridden decision making in a complex adaptive system (CAS) - The Additional Duty Hours Allowance in Ghana." *Health Policy and Planning*, 27(SUPPL. 4). https://doi.org/10.1093/heapol/czs083.

Ahiablame, L. M., Engel, B. A., & Chaubey, I. (2012). "Effectiveness of low impact development practices: Literature review and suggestions for future research." *Water, Air, and Soil Pollution*, 223(7). https://doi.org/10.1007/s11270-012-1189-2.

Ahmad, S. S., & Simonovic, S. P. (2015). "System dynamics and hydrodynamic modelling approaches for spatial and temporal analysis of flood risk." *International Journal of River Basin Management*, 13(4). https://doi.org/10.1080/15715124.2015.1016954.

Aho, M., & Sarkozy-Banoczy, S. (2020). "Resilient Houston." Retrieved from https://www.houstontx.gov/mayor/Resilient-Houston-20200518-single-page.pdf.

Alamdari, N., & Sample, D. J. (2019). "A multiobjective simulation-optimization tool for assisting in urban watershed restoration planning." *Journal of Cleaner Production*, 213. https://doi.org/10.1016/j.jclepro.2018.12.108.

Allen, P. M. (1988). “Dynamic models of evolving systems.” *System Dynamics Review*, 4(1–2). https://doi.org/10.1002/sdr.4260040107.

Alves, A., Gersonius, B., Sanchez, A., Vojinovic, Z., & Kapelan, Z. (2018). “Multi-criteria Approach for Selection of Green and Grey Infrastructure to Reduce Flood Risk and Increase CO-benefits.” *Water Resources Management*, 32(7). https://doi.org/10.1007/s11269-018-1943-3.

Alves, A., Gersonius, B., Kapelan, Z., Vojinovic, Z., & Sanchez, A. (2019). “Assessing the Co-Benefits of green-blue-grey infrastructure for sustainable urban flood risk management.” *Journal of Environmental Management*, 239. https://doi.org/10.1016/j.jenvman.2019.03.036.

Ames, D. P., Horsburgh, J. S., Cao, Y., Kadlec, J., Whiteaker, T., & Valentine, D. (2012). “HydroDesktop: Web services-based software for hydrologic data discovery, download, visualization, and analysis.” *Environmental Modelling and Software*, 37. https://doi.org/10.1016/j.envsoft.2012.03.013.

Andersen, D. F., & Richardson, G. P. (1997). “Scripts for group model building.” System Dynamics Review. https://doi.org/10.1002/(sici)1099-1727(199722)13:2<107::aid-sdr120>3.0.co;2-7.

Anderson, V., & Gough, W. A. (2020). “Evaluating the potential of nature-based solutions to reduce ozone, nitrogen dioxide, and carbon dioxide through a multi-type green infrastructure study in Ontario, Canada.” *City and Environment Interactions*, 6. https://doi.org/10.1016/j.cacint.2020.100043.

Astell-Burt, T., & Feng, X. (2021). “Urban green space, tree canopy and prevention of cardiometabolic diseases: A multilevel longitudinal study of 46 786 Australians.” *International Journal of Epidemiology*, 49(3). https://doi.org/10.1093/IJE/DYZ239.

Axelrod, R. (1976). Structure of decision: The cognitive maps of political elites *Structure of Decision: The Cognitive Maps of Political Elites*. https://doi.org/10.2307/2616237.

Bahri, M. (2020). “Analysis of the water, energy, food and land nexus using the system archetypes: A case study in the Jatiluhur reservoir, West Java, Indonesia.” *Science of the Total Environment*, 716. https://doi.org/10.1016/j.scitotenv.2020.137025.

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Yan, K., Brandimarte, L., & Blöschl, G. (2015). “Debates - Perspectives on socio-hydrology: Capturing feedbacks between physical and social processes.” *Water Resources Research*. https://doi.org/10.1002/2014WR016416.

Di Baldassarre, G., Sivapalan, M., Rusca, M., Cudennec, C., Garcia, M., Kreibich, H., Konar, M., Mondino, E., Mård, J., Pande, S., Sanderson, M. R., Tian, F., Viglione, A., Wei, J., Wei, Y., Yu, D. J., Srinivasan, V., & Blöschl, G. (2019). “Sociohydrology: Scientific Challenges in Addressing the Sustainable Development Goals.” *Water Resources Research*, 55(8). https://doi.org/10.1029/2018WR023901.

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

Barco, J., Wong, K. M., & Stenstrom, M. K. (2009). “Closure to “Automatic Calibration of the US EPA SWMM Model for a Large Urban Catchment” by Janet Barco, Kenneth M. Wong, and Michael K. Stenstrom.” *Journal of Hydraulic Engineering*, 135(12). https://doi.org/10.1061/(asce)hy.1943-7900.0000121.

Barlas, Y. (2002). “System Dynamics: Systemic feedback modeling for policy analysis.” *Knowledge for Sustainable Development: An Insight into the Encyclopedia of Life Support Systems*.

Barrett, D. (2019). “NOAA Atlas 14 PCPM IDF Curves Update.” American Council of Engineering (ACEC) Houston. Retrieved from https://acechouston.org/wp-content/uploads/2017/10/HDR-IDF-Curves-Memo.pdf.

Berardi, U., GhaffarianHoseini, A. H., & GhaffarianHoseini, A. (2014). “State-of-the-art analysis of the environmental benefits of green roofs.” *Applied Energy*. https://doi.org/10.1016/j.apenergy.2013.10.047.

van den Berg, A. E., Maas, J., Verheij, R. A., & Groenewegen, P. P. (2010). “Green space as a buffer between stressful life events and health.” *Social Science and Medicine*, 70(8). https://doi.org/10.1016/j.socscimed.2010.01.002.

Bernagros, J. T., Pankani, D., Struck, S. D., & Deerhake, M. E. (2021). “Estimating Regionalized Planning Costs of Green Infrastructure and Low-Impact Development Stormwater Management Practices: Updates to the US Environmental Protection Agency’s National Stormwater Calculator.” *Journal of Sustainable Water in the Built Environment*, 7(2). https://doi.org/10.1061/jswbay.0000934.

Bissonnette, J. F., Dupras, J., Messier, C., Lechowicz, M., Dagenais, D., Paquette, A., Jaeger, J. A. G., & Gonzalez, A. (2018). “Moving forward in implementing green

infrastructures: Stakeholder perceptions of opportunities and obstacles in a major North American metropolitan area." *Cities*, 81. https://doi.org/10.1016/j.cities.2018.03.014.

Blair, P., & Buytaert, W. (2016). "Socio-hydrological modelling: A review asking "why, what and how?"" *Hydrology and Earth System Sciences*, 20(1). https://doi.org/10.5194/hess-20-443-2016.

Bloom, M. F., Asakura, K., Clements, J., & Valderrama, A. (2019). "Houston Incentives for Green Development." Retrieved from https://www.houstontx.gov/igd/documents/igd-report-final.pdf.

Boano, F., Caruso, A., Costamagna, E., Ridolfi, L., Fiore, S., Demichelis, F., Galvão, A., Pisoeiro, J., Rizzo, A., & Masi, F. (2020). "A review of nature-based solutions for greywater treatment: Applications, hydraulic design, and environmental benefits." *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2019.134731.

van den Bosch, M., & Ode Sang (2017). "Urban natural environments as nature-based solutions for improved public health – A systematic review of reviews." *Environmental Research*, 158. https://doi.org/10.1016/j.envres.2017.05.040.

Bouziotas, D., & Ertsen, M. (2017). "Socio-hydrology from the bottom up: A template for agent-based modeling in irrigation systems." *Hydrology and Earth System Sciences Discussions*. https://doi.org/10.5194/hess-2017-107.

Bowen, K. J., Parry, M., Barrett, M. A., Miller, D., Frumkin, H., Peen, J., Schoevers, R. A., Beekman, A. T., Dekker, J., Sandifer, P. A., Sutton-Grier, A. E., Ward, B. P., Gascon, M., Triguero-Mas, M., Martínez, D., Dadvand, P., Rojas-Rueda, D., Plasència, A., Nieuwenhuijsen, M. J., Wolch, J. R., Byrne, J., & Newell, J. P. (2014).

"The evidence base for linkages between green infrastructure, public health and economic benefit." *Ecosystem Services*.

Bowler, D. E., Buyung-Ali, L., Knight, T. M., & Pullin, A. S. (2010). "Urban greening to cool towns and cities: A systematic review of the empirical evidence." *Landscape and Urban Planning*. https://doi.org/10.1016/j.landurbplan.2010.05.006.

Boyce, J. K., Zwickl, K., & Ash, M. (2016). "Measuring environmental inequality." *Ecological Economics*, 124. https://doi.org/10.1016/j.ecolecon.2016.01.014.

Boyd, D. S., & Foody, G. M. (2011). "An overview of recent remote sensing and GIS based research in ecological informatics." *Ecological Informatics*, 6(1). https://doi.org/10.1016/j.ecoinf.2010.07.007.

Branas, C. C., Cheney, R. A., MacDonald, J. M., Tam, V. W., Jackson, T. D., & Ten Havey, T. R. (2011). "A difference-in-differences analysis of health, safety, and greening vacant urban space." *American Journal of Epidemiology*, 174(11). https://doi.org/10.1093/aje/kwr273.

Bratman, G. N., Anderson, C. B., Berman, M. G., Cochran, B., de Vries, S., Flanders, J., Folke, C., Frumkin, H., Gross, J. J., Hartig, T., Kahn, P. H., Kuo, M., Lawler, J. J., Levin, P. S., Lindahl, T., Meyer-Lindenberg, A., Mitchell, R., Ouyang, Z., Roe, J., Scarlett, L., Smith, J. R., van den Bosch, M., Wheeler, B. W., White, M. P., Zheng, H., & Daily, G. C. (2019). "Nature and mental health: An ecosystem service perspective." *Science Advances*. https://doi.org/10.1126/sciadv.aax0903.

Brennan, L. K., Sabounchi, N. S., Kemner, A. L., & Hovmand, P. (2015). "Systems thinking in 49 communities related to healthy eating, active living, and childhood obesity." *Journal of Public Health Management and Practice : JPHMP*, 21.

https://doi.org/10.1097/PHH.0000000000000248.

Brown, S. C., Lombard, J., Wang, K., Byrne, M. M., Toro, M., Plater-Zyberk, E., Feaster, D. J., Kardys, J., Nardi, M. I., Perez-Gomez, G., Pantin, H. M., & Szapocznik, J. (2016). "Neighborhood greenness and chronic health conditions in medicare beneficiaries." *American Journal of Preventive Medicine*, 51(1). https://doi.org/10.1016/j.amepre.2016.02.008.

Bueno, S., & Salmeron, J. L. (2009). "Benchmarking main activation functions in fuzzy cognitive maps." *Expert Systems with Applications*, 36(3 PART 1). https://doi.org/10.1016/j.eswa.2008.06.072.

Bureš, V. (2017). "A method for simplification of complex group causal loop diagrams based on endogenisation, encapsulation and order-oriented reduction." *Systems*, 5(3). https://doi.org/10.3390/systems5030046.

Bureš, V., Otčenášková, T., Zanker, M., & Nehéz, M. (2020). "The most common issues in development of causal-loop diagrams and stock-and-flow diagrams." *International Journal of Intelligent Engineering Informatics*, 8(5/6). https://doi.org/10.1504/ijiei.2020.115722.

Butler, C., & Adamowski, J. (2015). "Empowering marginalized communities in water resources management: Addressing inequitable practices in Participatory Model Building." *Journal of Environmental Management*, 153. https://doi.org/10.1016/j.jenvman.2015.02.010.

Capano, G., & Howlett, M. (2019). "Causal logics and mechanisms in policy design: How and why adopting a mechanistic perspective can improve policy design." *Public Policy and Administration*. https://doi.org/10.1177/0952076719827068.

Castro, C. V., & Maidment, D. R. (2020). "GIS preprocessing for rapid initialization of HEC-HMS hydrological basin models using web-based data services." *Environmental Modelling and Software*, 130. https://doi.org/10.1016/j.envsoft.2020.104732.

CDC (2016). "CDC SVI 2016 Documentation." Retrieved from https://svi.cdc.gov/Documents/Data/2016_SVI_Data/SVI2016Documentation.pdf.

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

Chamberlain, A. M., Finney Rutten, L. J., Wilson, P. M., Fan, C., Boyd, C. M., Jacobson, D. J., Rocca, W. A., & St Sauver, J. L. (2020). "Neighborhood socioeconomic disadvantage is associated with multimorbidity in a geographically-defined community." *BMC Public Health*, 20(1). https://doi.org/10.1186/s12889-019-8123-0.

CHI (2014). "PCSWMM Support: Transect creator." Computational Hydraulics International. Retrieved from https://support.chiwater.com/79610/transect-creator.

CHI (2015). "PCSWMM User's Manual Support: Sensitivity-based Radio Tuning Calibration (SRTC)." Computational Hydraulics International. Retrieved from https://support.chiwater.com/78922/srtc.

CHI (2020). "PCSWMM Support Manual: Error Functions." Computational Hydraulics International. Retrieved from https://support.chiwater.com/79652/error-functions.

Cho, J. H., & Lee, J. H. (2014). "Multi-objective waste load allocation model for optimizing waste load abatement and inequality among waste dischargers." *Water,*

Air, and Soil Pollution, 225(3). https://doi.org/10.1007/s11270-014-1892-2.

Choi, J., Hwang, M., Kim, G., Seong, J., & Ahn, J. (2016). "Supporting the measurement of the United Nations' sustainable development goal 11 through the use of national urban information systems and open geospatial technologies: A case study of south Korea." *Open Geospatial Data, Software and Standards*, 1(1). https://doi.org/10.1186/s40965-016-0005-0.

Choi, K. S., & Ball, J. E. (2002). "Parameter estimation for urban runoff modelling." *Urban Water*, 4(1). https://doi.org/10.1016/S1462-0758(01)00072-3.

City of Houston (2020). "Houston Climate Action Plan." Retrieved from http://greenhoustontx.gov/climateactionplan/CAP-April2020.pdf.

Clary, J., Leisenring, M., & Strecker, E. (2020). "International Stormwater BMP Database: 2020 Summary Statistics." International Stormwater BMP Database. Retrieved from https://www.waterrf.org/system/files/resource/2020-11/DRPT-4968_0.pdf.

COH (2019a). "City of Houston Design Manual: Chapter 9, Stormwater Design Requirements, Section 9.15." City of Houston Public Works. Retrieved from https://acechouston.org/wp-content/uploads/2019/03/ch-9-including-ch13-2019.pdf.

COH (2019b). "Infrastructure Design Manual 2019, Section 9.2.01.B.1, Design Rainfall Events." City of Houston Public Works. Retrieved from https://www.houstonpermittingcenter.org/media/4121/download.

COH (2021). "City of Houston Data Hub." City of Houston. Retrieved from https://cohgis-mycity.opendata.arcgis.com/.

Cohen-Shacham, E., Andrade, A., Dalton, J., Dudley, N., Jones, M., Kumar, C., Maginnis, S., Maynard, S., Nelson, C. R., Renaud, F. G., Welling, R., & Walters, G. (2019). "Core principles for successfully implementing and upscaling Nature-based Solutions." *Environmental Science and Policy*. https://doi.org/10.1016/j.envsci.2019.04.014.

Coletta, V. R., Pagano, A., Pluchinotta, I., Fratino, U., Scrieciu, A., Nanu, F., & Giordano, R. (2021). "Causal Loop Diagrams for supporting Nature Based Solutions participatory design and performance assessment." *Journal of Environmental Management*, 280. https://doi.org/10.1016/j.jenvman.2020.111668.

Collins, R. D., de Neufville, R., Claro, J., Oliveira, T., & Pacheco, A. P. (2013). "Forest fire management to avoid unintended consequences: A case study of Portugal using system dynamics." *Journal of Environmental Management*, 130. https://doi.org/10.1016/j.jenvman.2013.08.033.

Cumming, G. S. (2011). Spatial resilience in social-ecological systems *Spatial Resilience in Social-Ecological Systems*. https://doi.org/10.1007-978-94-007-0307-0.

Dangermond, J. (2019). "The Emergence of a Geospatial Cloud." https://doi.org/https://www.esri.com/about/newsroom/arcnews/the-emergence-of-a-geospatial-cloud/

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). "A fast and elitist multiobjective genetic algorithm: NSGA-II." *IEEE Transactions on Evolutionary Computation*, 6(2). https://doi.org/10.1109/4235.996017.

Demuzere, M., Orru, K., Heidrich, O., Olazabal, E., Geneletti, D., Orru, H., Bhave, A. G., Mittal, N., Feliu, E., & Faehnle, M. (2014). "Mitigating and adapting to climate

change: Multi-functional and multi-scale assessment of green urban infrastructure." *Journal of Environmental Management*, 146. https://doi.org/10.1016/j.jenvman.2014.07.025.

Derkzen, M. L., van Teeffelen, A. J. A., & Verburg, P. H. (2017). "Green infrastructure for urban climate adaptation: How do residents' views on climate impacts and green infrastructure shape adaptation preferences?" *Landscape and Urban Planning*, 157. https://doi.org/10.1016/j.landurbplan.2016.05.027.

Despart, Z. (2019). "Harris County approves "worst-first" priority model for flood bond projects." Houston Chronicle. Retrieved from https://www.houstonchronicle.com/news/houston-texas/houston/article/Harris-County-approves-worst-first-priority-14383015.php.

Dhakal, K. P., & Chevalier, L. R. (2016). "Urban Stormwater Governance: The Need for a Paradigm Shift." *Environmental Management*, 57(5). https://doi.org/10.1007/s00267-016-0667-5.

Druckman, A., & Jackson, T. (2008). "Measuring resource inequalities: The concepts and methodology for an area-based Gini coefficient." *Ecological Economics*, 65(2). https://doi.org/10.1016/j.ecolecon.2007.12.013.

Du, E., Cai, X., Wu, F., Foster, T., & Zheng, C. (2021). "Exploring the impacts of the inequality of water permit allocation and farmers' behaviors on the performance of an agricultural water market." *Journal of Hydrology*, 599. https://doi.org/10.1016/j.jhydrol.2021.126303.

Duan, H. F., Li, F., & Yan, H. (2016). “Multi-Objective Optimal Design of Detention Tanks in the Urban Stormwater Drainage System: LID Implementation and Analysis.” *Water Resources Management*, 30(13). https://doi.org/10.1007/s11269-016-1444-1.

Dzhambov, A., & Dimitrova, D. (2014). “Urban green spaces′ effectiveness as a psychological buffer for the negative health impact of noise pollution: A systematic review.” *Noise and Health*. https://doi.org/10.4103/1463-1741.134916.

Eberlein, R. L., & Peterson, D. W. (1992). “Understanding models with Vensim™.” *European Journal of Operational Research*, 59(1). https://doi.org/10.1016/0377-2217(92)90018-5.

Eckart, K., McPhee, Z., & Bolisetti, T. (2017). “Performance and implementation of low impact development – A review.” *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2017.06.254.

Ellis, J. B., & Lundy, L. (2016). “Implementing sustainable drainage systems for urban surface water management within the regulatory framework in England and Wales.” *Journal of Environmental Management*, 183. https://doi.org/10.1016/j.jenvman.2016.09.022.

Engel, B. A., Choi, J. Y., Harbor, J., & Pandey, S. (2003). “Web-based DSS for hydrologic impact evaluation of small watershed land use changes.” *Computers and Electronics in Agriculture*, 39(3). https://doi.org/10.1016/S0168-1699(03)00078-4.

Esri (2017). Add Custom Widgets to Web AppBuilder for ArcGIS Developer Edition. https://doi.org/https://www.esri.com/about/newsroom/arcwatch/add-custom-widgets-to-web-appbuilder-for-arcgis-developer-edition/.

Esri (2021a). ArcGIS Living Atlas of the World. https://doi.org/https://livingatlas.arcgis.com/en/home/.

Esri (2021b). Terrain. https://doi.org/https://uh1.maps.arcgis.com/home/item.html?id=58a541efc59545e6b7137f961d7de883.

Feng, Q., Flanagan, D. C., Engel, B. A., Yang, L., & Chen, L. (2020). "GeoAPEXOL, a web GIS interface for the Agricultural Policy Environmental eXtender (APEX) model enabling both field and small watershed simulation." *Environmental Modelling and Software*, 123. https://doi.org/10.1016/j.envsoft.2019.104569.

Fenner, R. (2017). "Spatial evaluation of multiple benefits to encourage multi-functional design of sustainable drainage in Blue-Green cities." *Water (Switzerland)*, 9(12). https://doi.org/10.3390/w9120953.

Fernald, A., Tidwell, V., Rivera, J., Rodríguez, S., Guldan, S., Steele, C., Ochoa, C., Hurd, B., Ortiz, M., Boykin, K., & Cibils, A. (2012). "Modeling sustainability of water, environment, livelihood, and culture in traditional irrigation communities and their linked watersheds." *Sustainability*, 4(11). https://doi.org/10.3390/su4112998.

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2020). "A Social Vulnerability Index for Disaster Management." *Journal of Homeland Security and Emergency Management*, 8(1). https://doi.org/10.2202/1547-7355.1792.

Flemons, P., Guralnick, R., Krieger, J., Ranipeta, A., & Neufeld, D. (2007). "A web-based GIS tool for exploring the world's biodiversity: The Global Biodiversity Information Facility Mapping and Analysis Portal Application (GBIF-MAPA)." *Ecological Informatics*, 2(1). https://doi.org/10.1016/j.ecoinf.2007.03.004.

Forrester, J. W. (1994). “System dynamics, systems thinking, and soft OR.” *System Dynamics Review*, 10(2–3). https://doi.org/10.1002/sdr.4260100211.

Frantzeskaki, N., McPhearson, T., Collier, M. J., Kendal, D., Bulkeley, H., Dumitru, A., Walsh, C., Noble, K., Van Wyk, E., Ordóñez, C., Oke, C., & Pintér, L. (2019). “Nature-based solutions for urban climate change adaptation: Linking science, policy, and practice communities for evidence-based decision-making.” *BioScience*, 69(6). https://doi.org/10.1093/biosci/biz042.

Frini, A., & Ben Amor, S. (2019). “MUPOM: A multi-criteria multi-period outranking method for decision-making in sustainable development context.” *Environmental Impact Assessment Review*, 76. https://doi.org/10.1016/j.eiar.2018.11.002.

Fu, B., Merritt, W. S., Croke, B. F. W., Weber, T. R., & Jakeman, A. J. (2019). “A review of catchment-scale water quality and erosion models and a synthesis of future prospects.” *Environmental Modelling and Software*. https://doi.org/10.1016/j.envsoft.2018.12.008.

Fuertes, E., Markevych, I., von Berg, A., Bauer, C. P., Berdel, D., Koletzko, S., Sugiri, D., & Heinrich, J. (2014). “Greenness and allergies: Evidence of differential associations in two areas in Germany.” *Journal of Epidemiology and Community Health*, 68(8). https://doi.org/10.1136/jech-2014-203903.

Gaál, L., Szolgay, J., Kohnová, S., Parajka, J., Merz, R., Viglione, A., & Blöschl, G. (2012). “Flood timescales: Understanding the interplay of climate and catchment processes through comparative hydrology.” *Water Resources Research*, 48(4). https://doi.org/10.1029/2011WR011509.

García, A. M., Santé, I., Loureiro, X., & Miranda, D. (2020). “Green infrastructure spatial planning considering ecosystem services assessment and trade-off analysis. Application at landscape scale in Galicia region (NW Spain).” *Ecosystem Services*, 43. https://doi.org/10.1016/j.ecoser.2020.101115.

Gascon, M., Triguero-Mas, M., Martínez, D., Dadvand, P., Rojas-Rueda, D., Plasència, A., & Nieuwenhuijsen, M. J. (2016). “Residential green spaces and mortality: A systematic review.” *Environment International*. https://doi.org/10.1016/j.envint.2015.10.013.

Gebrai, Y., Ghebremichael, K., & Mihelcic, J. R. (2021). “A systems approach to analyzing food, energy, and water uses of a multifunctional crop: A review.” *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2021.148254.

Gersonius, B., van Buuren, A., Zethof, M., & Kelder, E. (2016). “Resilient flood risk strategies: Institutional preconditions for implementation.” *Ecology and Society*, 21(4). https://doi.org/10.5751/ES-08752-210428.

Giacomoni, M. H., & Joseph, J. (2017). “Multi-Objective Evolutionary Optimization and Monte Carlo Simulation for Placement of Low Impact Development in the Catchment Scale.” *Journal of Water Resources Planning and Management*, 143(9). https://doi.org/10.1061/(asce)wr.1943-5452.0000812.

Giacomoni, M. H., & Zechman, E. M. (2010). A complex adaptive systems approach to simulate urban water resources sustainability In *World Environmental and Water Resources Congress 2010: Challenges of Change - Proceedings of the World Environmental and Water Resources Congress 2010*. https://doi.org/10.1061/41114(371)262.

Gilbert-Norton, L., WILSON, R., STEVENS, J. R., & BEARD, K. H. (2010). "A Meta-Analytic Review of Corridor Effectiveness." *Conservation Biology*, 24(3). https://doi.org/10.1111/j.1523-1739.2010.01450.x.

Gini, C. W. (1912). "Variability and Mutability, contribution to the study of statistical distributions and relations." *Studi Economico-Giuridici Della Studi Economico-Giuricici Della R. Università de Cagliari*.

Giordano, R., Pluchinotta, I., Pagano, A., Scrieciu, A., & Nanu, F. (2020). "Enhancing nature-based solutions acceptance through stakeholders' engagement in co-benefits identification and trade-offs analysis." *Science of the Total Environment*, 713. https://doi.org/10.1016/j.scitotenv.2020.136552.

Giordano, Raffaele, Mysiak, J., Raziyeh, F., & Vurro, M. (2007). "An integration between cognitive map and causal loop diagram for knowledge structuring in river basin management." *1st International Conference on Adaptive & Integrated Water Management*.

Giorgi, G. M., & Gigliarano, C. (2017). "The gini concentration index: A review of the inference literature." *Journal of Economic Surveys*, 31(4). https://doi.org/10.1111/joes.12185.

GLA (2018). "Green Infrastructure Focus Map: Briefing 1." London.

Glykas, M. (2005). Fuzzy Cognitive Maps: Advances in Theory, Methodologies, Tools and Applications *Soft Computing* (Vol. 247).

Golden, H. E., & Hoghooghi, N. (2018). "Green infrastructure and its catchment-scale effects: An emerging science." *Wiley Interdisciplinary Reviews: Water*, 5(1). https://doi.org/10.1002/wat2.1254.

Gómez Martín, E., Giordano, R., Pagano, A., van der Keur, P., & Máñez Costa, M. (2020). "Using a system thinking approach to assess the contribution of nature based solutions to sustainable development goals." *Science of the Total Environment*, 738. https://doi.org/10.1016/j.scitotenv.2020.139693.

de Gooyert, V., Rouwette, E., van Kranenburg, H., Freeman, E., & van Breen, H. (2016). "Sustainability transition dynamics: Towards overcoming policy resistance." *Technological Forecasting and Social Change*, 111. https://doi.org/10.1016/j.techfore.2016.06.019.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). "Google Earth Engine: Planetary-scale geospatial analysis for everyone." *Remote Sensing of Environment*, 202. https://doi.org/10.1016/j.rse.2017.06.031.

Granell, C., Díaz, L., & Gould, M. (2010). "Service-oriented applications for environmental models: Reusable geospatial services." *Environmental Modelling and Software*, 25(2). https://doi.org/10.1016/j.envsoft.2009.08.005.

Granell, C., Havlik, D., Schade, S., Sabeur, Z., Delaney, C., Pielorz, J., Usländer, T., Mazzetti, P., Schleidt, K., Kobernus, M., Havlik, F., Bodsberg, N. R., Berre, A., & Mon, J. L. (2016). "Future Internet technologies for environmental applications." *Environmental Modelling and Software*, 78. https://doi.org/10.1016/j.envsoft.2015.12.015.

Gray, S. A., Zanre, E., & Gray, S. R. J. (2014). "Fuzzy cognitive maps as representations of mental models and group beliefs." *Intelligent Systems Reference Library*, 54. https://doi.org/10.1007/978-3-642-39739-4_2.

Gray, Steven A., Gray, S., Cox, L. J., & Henly-Shepard, S. (2013). Mental Modeler: A fuzzy-logic cognitive mapping modeling tool for adaptive environmental management In *Proceedings of the Annual Hawaii International Conference on System Sciences*. https://doi.org/10.1109/HICSS.2013.399.

Gray, Steven A., Gray, S., de Kok, J. L., Helfgott, A. E. R., O'Dwyer, B., Jordan, R., & Nyaki, A. (2015). "Using fuzzy cognitive mapping as a participatory approach to analyze change, preferred states, and perceived resilience of social-ecological systems." *Ecology and Society*, 20(2). https://doi.org/10.5751/ES-07396-200211.

Grineski, S., Collins, T. W., Chakraborty, J., & Montgomery, M. (2015). "Hazardous air pollutants and flooding: A comparative interurban study of environmental injustice." *GeoJournal*, 80(1). https://doi.org/10.1007/s10708-014-9542-1.

Groves-Kirkby, C. J., Denman, A. R., & Phillips, P. S. (2009). "Lorenz Curve and Gini Coefficient: Novel tools for analysing seasonal variation of environmental radon gas." *Journal of Environmental Management*, 90(8). https://doi.org/10.1016/j.jenvman.2009.01.003.

Guo, H., Liu, Z., Jiang, H., Wang, C., Liu, J., & Liang, D. (2017). "Big Earth Data: A new challenge and opportunity for Digital Earth's development." *International Journal of Digital Earth*. https://doi.org/10.1080/17538947.2016.1264490.

Hamouz, V., Møller-Pedersen, P., & Muthanna, T. M. (2020). "Modelling runoff reduction through implementation of green and grey roofs in urban catchments using PCSWMM." *Urban Water Journal*, 17(9). https://doi.org/10.1080/1573062X.2020.1828500.

Hansen, R., Olafsson, A. S., van der Jagt, A. P. N., Rall, E., & Pauleit, S. (2019). "Planning multifunctional green infrastructure for compact cities: What is the state of practice?" *Ecological Indicators*, 96. https://doi.org/10.1016/j.ecolind.2017.09.042.

Harich, J. (2010). "Change resistance as the crux of the environmental sustainability problem." *System Dynamics Review*, 26(1). https://doi.org/10.1002/sdr.431.

HCFCD (2019). "Model and map management system (M3)." *Harris County Flood Control District*. Retrieved from https://www.m3models.org/.

HCFCD (2020). "Wet bottom detention basins with water quality features." Harris County Flood Control District. Retrieved from https://www.hcfcd.org/Portals/62/Our Programs/designguidelineswetbottombasins_final.pdf?ver=2020-02-06-123205-900.

HCFCD (2021). "Harris County Flood Warning System." Harris County Flood Control District. Retrieved from https://www.harriscountyfws.org/.

Heerink, N., Mulatu, A., & Bulte, E. (2001). "Income inequality and the environment: Aggregation bias in environmental Kuznets curves." *Ecological Economics*, 38(3). https://doi.org/10.1016/S0921-8009(01)00171-9.

Henly-Shepard, S., Gray, S. A., & Cox, L. J. (2015). "The use of participatory modeling to promote social learning and facilitate community disaster planning." *Environmental Science and Policy*, 45. https://doi.org/10.1016/j.envsci.2014.10.004.

Hirshberg, E. L., Wilson, E. L., Stanfield, V., Kuttler, K. G., Majercik, S., Beesley, S. J., Orme, J., Hopkins, R. O., & Brown, S. M. (2019). "Impact of Critical Illness on Resource Utilization: A Comparison of Use in the Year Before and After ICU Admission." *Critical Care Medicine*, 47(11). https://doi.org/10.1097/CCM.0000000000003970.

House-Peters, L. A., & Chang, H. (2011). “Urban water demand modeling: Review of concepts, methods, and organizing principles.” *Water Resources Research*, 47(5). https://doi.org/10.1029/2010WR009624.

Hovmand, P., Rouwette, E., Andersen, D. F., Richardson, G. P., Calhoun, A., Rux, K., & Hower, T. (2011). Scriptapedia: A handbook of scripts for developing structured group model building sessions In *Proceedings of the 2011 International System Dynamics Conference*.

Hu, Z., Chen, Y., Yao, L., Wei, C., & Li, C. (2016). “Optimal allocation of regional water resources: From a perspective of equity-efficiency tradeoff.” *Resources, Conservation and Recycling*, 109. https://doi.org/10.1016/j.resconrec.2016.02.001.

Huang, L., Li, X., Fang, H., Yin, D., Si, Y., Wei, J., Liu, J., Hu, X., & Zhang, L. (2019). “Balancing social, economic and ecological benefits of reservoir operation during the flood season: A case study of the Three Gorges Project, China.” *Journal of Hydrology*, 572. https://doi.org/10.1016/j.jhydrol.2019.03.009.

Huong, H. T. L., & Pathirana, A. (2013). “Urbanization and climate change impacts on future urban flooding in Can Tho city, Vietnam.” *Hydrology and Earth System Sciences*, 17(1). https://doi.org/10.5194/hess-17-379-2013.

Iadanza, C., Trigila, A., Starace, P., Dragoni, A., Biondo, T., & Roccisano, M. (2021). “IdroGEO: A collaborative web mapping application based on REST API services and open data on landslides and floods in Italy.” *ISPRS International Journal of Geo-Information*, 10(2). https://doi.org/10.3390/ijgi10020089.

Inam, A., Adamowski, J., Halbe, J., & Prasher, S. (2015). “Using causal loop diagrams for the initialization of stakeholder engagement in soil salinity management in

agricultural watersheds in developing countries: A case study in the Rechna Doab watershed, Pakistan." *Journal of Environmental Management*, 152. https://doi.org/10.1016/j.jenvman.2015.01.052.

Ingraham, N. E., Purcell, L. N., Karam, B. S., Dudley, R. A., Usher, M. G., Warlick, C. A., Allen, M. L., Melton, G. B., Charles, A., & Tignanelli, C. J. (2021). "Racial and Ethnic Disparities in Hospital Admissions from COVID-19: Determining the Impact of Neighborhood Deprivation and Primary Language." *Journal of General Internal Medicine*. https://doi.org/10.1007/s11606-021-06790-w.

Jacobson, A., Milman, A. D., & Kammen, D. M. (2005). "Letting the (energy) Gini out of the bottle: Lorenz curves of cumulative electricity consumption and Gini coefficients as metrics of energy distribution and equity." *Energy Policy*, 33(14). https://doi.org/10.1016/j.enpol.2004.02.017.

James, W. (2003). "Rules for responsible modeling." Computational Hydraulics International. Retrieved from https://www.chiwater.com/Files/R184_CHI_Rules.pdf.

Jarden, K. M., Jefferson, A. J., & Grieser, J. M. (2016). "Assessing the effects of catchment-scale urban green infrastructure retrofits on hydrograph characteristics." *Hydrological Processes*, 30(10). https://doi.org/10.1002/hyp.10736.

Jato-Espino, D., Charlesworth, S. M., Bayon, J. R., & Warwick, F. (2016). "Rainfall-runoff simulations to assess the potential of suds for mitigating flooding in highly urbanized catchments." *International Journal of Environmental Research and Public Health*, 13(1). https://doi.org/10.3390/ijerph13010149.

de Jesús Arce-Mojica, T., Nehren, U., Sudmeier-Rieux, K., Miranda, P. J., & Anhuf, D. (2019). "Nature-based solutions (NbS) for reducing the risk of shallow landslides:

Where do we stand?" *International Journal of Disaster Risk Reduction*. https://doi.org/10.1016/j.ijdrr.2019.101293.

Jetter, A., & Schweinfort, W. (2011). "Building scenarios with Fuzzy Cognitive Maps: An exploratory study of solar energy." *Futures*, 43(1). https://doi.org/10.1016/j.futures.2010.05.002.

Jin, S., Homer, C., Yang, L., Danielson, P., Dewitz, J., Li, C., Zhu, Z., Xian, G., & Howard, D. (2019). "Overall methodology design for the United States national land cover database 2016 products." *Remote Sensing*, 11(24). https://doi.org/10.3390/rs11242971.

Jones, N. A., Ross, H., Lynam, T., Perez, P., & Leitch, A. (2011). "Mental models: An interdisciplinary synthesis of theory and methods." *Ecology and Society*, 16(1). https://doi.org/10.5751/ES-03802-160146.

Josa, I., & Aguado, A. (2020). "Measuring Unidimensional Inequality: Practical Framework for the Choice of an Appropriate Measure." *Social Indicators Research*, 149(2). https://doi.org/10.1007/s11205-020-02268-0.

Kabisch, N., Frantzeskaki, N., Pauleit, S., Naumann, S., Davis, M., Artmann, M., Haase, D., Knapp, S., Korn, H., Stadler, J., Zaunberger, K., & Bonn, A. (2016). "Nature-based solutions to climate change mitigation and adaptation in urban areas: Perspectives on indicators, knowledge gaps, barriers, and opportunities for action." *Ecology and Society*, 21(2). https://doi.org/10.5751/ES-08373-210239.

Kaczynski, A. T., & Henderson, K. A. (2007). "Environmental correlates of physical activity: A review of evidence about parks and recreation." *Leisure Sciences*. https://doi.org/10.1080/01490400701394865.

Kaljonen, M., Varjopuro, R., Giełczewski, M., & Iital, A. (2012). “Seeking policy-relevant knowledge: A comparative study of the contextualisation of participatory scenarios for the Narew River and Lake Peipsi.” *Environmental Science and Policy*, 15(1). https://doi.org/10.1016/j.envsci.2011.10.006.

Kandakoglu, A., Frini, A., & Ben Amor, S. (2019). “Multicriteria decision making for sustainable development: A systematic review.” *Journal of Multi-Criteria Decision Analysis*, 26(5–6). https://doi.org/10.1002/mcda.1682.

Kaykhosravi, S., Abogadil, K., Khan, U. T., & Jadidi, M. A. (2019). “The low-impact Development Demand Index: A new approach to identifying locations for LID.” *Water (Switzerland)*, 11(11). https://doi.org/10.3390/w11112341.

Keesstra, S., Nunes, J., Novara, A., Finger, D., Avelar, D., Kalantari, Z., & Cerdà, A. (2018). “The superior effect of nature based solutions in land management for enhancing ecosystem services.” *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2017.08.077.

Khalil, A., Hanich, L., Hakkou, R., & Lepage, M. (2014). “GIS-based environmental database for assessing the mine pollution: A case study of an abandoned mine site in Morocco.” *Journal of Geochemical Exploration*, 144(PC). https://doi.org/10.1016/j.gexplo.2014.03.023.

Kim, M., You, S., Chon, J., & Lee, J. (2017). “Sustainable land-use planning to improve the coastal resilience of the social-ecological landscape.” *Sustainability (Switzerland)*, 9(7). https://doi.org/10.3390/su9071086.

Kind, A. J. H., & Buckingham, W. R. (2018). “Making Neighborhood-Disadvantage Metrics Accessible — The Neighborhood Atlas.” *New England Journal of Medicine*, 378(26). https://doi.org/10.1056/nejmp1802313.

Kitsiou, D., Patera, A., Tsegas, G., & Nitis, T. (2021). “A webgis application to assess seawater quality: A case study in a coastal area in the northern aegean sea.” *Journal of Marine Science and Engineering*, 9(1). https://doi.org/10.3390/jmse9010033.

Knighton, A. J., Savitz, L., Belnap, T., Stephenson, B., & VanDerslice, J. (2016). “Introduction of an Area Deprivation Index Measuring Patient Socio-economic Status in an Integrated Health System: Implications for Population Health.” *EGEMs (Generating Evidence & Methods to Improve Patient Outcomes)*, 4(3). https://doi.org/10.13063/2327-9214.1238.

Kok, K. (2009). “The potential of Fuzzy Cognitive Maps for semi-quantitative scenario development, with an example from Brazil.” *Global Environmental Change*, 19(1). https://doi.org/10.1016/j.gloenvcha.2008.08.003.

Kokkinos, K., Karayannis, V., & Moustakas, K. (2020). “Circular bio-economy via energy transition supported by Fuzzy Cognitive Map modeling towards sustainable low-carbon environment.” *Science of the Total Environment*, 721. https://doi.org/10.1016/j.scitotenv.2020.137754.

Konar, M., Garcia, M., Sanderson, M. R., Yu, D. J., & Sivapalan, M. (2019). “Expanding the Scope and Foundation of Sociohydrology as the Science of Coupled Human-Water Systems.” *Water Resources Research*. https://doi.org/10.1029/2018WR024088.

Kosko, B. (1986). “Fuzzy cognitive maps.” *International Journal of Man-Machine Studies*, 24(1). https://doi.org/10.1016/S0020-7373(86)80040-2.

Kotir, J. H. (2020). Managing and Sustaining the Coupled Water-Land-Food Systems in the Context of Global Change: How Qualitative System Dynamic Modelling Can Assist in Understanding and Designing High-Leverage Interventions In *Natural Resources Management and Biological Sciences*.

Kotir, J. H., Smith, C., Brown, G., Marshall, N., & Johnstone, R. (2016). “A system dynamics simulation model for sustainable water resources management and agricultural development in the Volta River Basin, Ghana.” *Science of the Total Environment*, 573. https://doi.org/10.1016/j.scitotenv.2016.08.081.

Kotir, J. H., Brown, G., Marshall, N., & Johnstone, R. (2017). “Systemic feedback modelling for sustainable water resources management and agricultural development: An application of participatory modelling approach in the Volta River Basin.” *Environmental Modelling and Software*, 88. https://doi.org/10.1016/j.envsoft.2016.11.015.

Koutsoyiannis, D., Kozonis, D., & Manetas, A. (1998). “A mathematical framework for studying rainfall intensity-duration-frequency relationships.” *Journal of Hydrology*, 206(1–2). https://doi.org/10.1016/S0022-1694(98)00097-3.

Krebs, G., Kokkonen, T., Valtanen, M., Koivusalo, H., & Setälä, H. (2013). “A high resolution application of a stormwater management model (SWMM) using genetic parameter optimization.” *Urban Water Journal*, 10(6). https://doi.org/10.1080/1573062X.2012.739631.

Kronenberg, J. (2015). “Why not to green a city? Institutional barriers to preserving urban ecosystem services.” *Ecosystem Services*, 12. https://doi.org/10.1016/j.ecoser.2014.07.002.

Kuil, L., Carr, G., Viglione, A., Prskawetz, A., & Blöschl, G. (2016). “Conceptualizing socio-hydrological drought processes: The case of the Maya collapse.” *Water Resources Research*, 52(8). https://doi.org/10.1002/2015WR018298.

Kuller, M., Bach, P. M., Ramirez-Lovering, D., & Deletic, A. (2017). “Framing water sensitive urban design as part of the urban form: A critical review of tools for best planning practice.” *Environmental Modelling and Software*. https://doi.org/10.1016/j.envsoft.2017.07.003.

Kurani, S. S., McCoy, R. G., Lampman, M. A., Doubeni, C. A., Finney Rutten, L. J., Inselman, J. W., Giblon, R. E., Bunkers, K. S., Stroebel, R. J., Rushlow, D., Chawla, S. S., & Shah, N. D. (2020). “Association of Neighborhood Measures of Social Determinants of Health With Breast, Cervical, and Colorectal Cancer Screening Rates in the US Midwest.” *JAMA Network Open*, 3(3). https://doi.org/10.1001/jamanetworkopen.2020.0618.

Langsdale, S. M., Beall, A., Carmichael, J., Cohen, S. J., Forster, C. B., & Neale, T. (2009). “Exploring the Implications of Climate Change on Water Resources through Participatory Modeling: Case Study of the Okanagan Basin, British Columbia.” *Journal of Water Resources Planning and Management*, 135(5). https://doi.org/10.1061/(asce)0733-9496(2009)135:5(373).

Lee, J. G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J. X., Shoemaker, L., & Lai, F. hsiung (2012). “A watershed-scale design optimization model for stormwater best

management practices." *Environmental Modelling and Software*, 37. https://doi.org/10.1016/j.envsoft.2012.04.011.

Lee, W. C. (1997). "Characterizing exposure-disease association in human populations using the Lorenz curve and Gini index." *Statistics in Medicine*, 16(7). https://doi.org/10.1002/(SICI)1097-0258(19970415)16:7<729::AID-SIM491>3.0.CO;2-A.

Lehmann, A., Guigoz, Y., Ray, N., Mancosu, E., Abbaspour, K. C., Rouholahnejad Freund, E., Allenbach, K., De Bono, A., Fasel, M., Gago-Silva, A., Bär, R., Lacroix, P., & Giuliani, G. (2017). "A web platform for landuse, climate, demography, hydrology and beach erosion in the Black Sea catchment." *Scientific Data*, 4. https://doi.org/10.1038/sdata.2017.87.

Levy, Z. F., Smardon, R. C., Bays, J. S., & Meyer, D. (2014). "A point source of a different color: Identifying a gap in united states regulatory policy for "green" CSO treatment using constructed wetlands." *Sustainability (Switzerland)*, 6(5). https://doi.org/10.3390/su6052392.

Li, H., Ding, L., Ren, M., Li, C., & Wang, H. (2017). "Sponge city construction in China: A survey of the challenges and opportunities." *Water (Switzerland)*, 9(9). https://doi.org/10.3390/w9090594.

Li, J., Deng, C., Li, Y., Li, Y., & Song, J. (2017). "Comprehensive Benefit Evaluation System for Low-Impact Development of Urban Stormwater Management Measures." *Water Resources Management*, 31(15). https://doi.org/10.1007/s11269-017-1776-5.

Li, Z., Dong, M., Wong, T., Wang, J., Kumar, A. J., & Singh, R. P. (2018). "Objectives and indexes for implementation of sponge cities-A case study of Changzhou City, China." *Water (Switzerland)*, 10(5). https://doi.org/10.3390/w10050623.

Liew, A. (2013). "DIKIW: Data, information, knowledge, intelligence, wisdom and their interrelationships." *Business Management Dynamics*, 2(10).

Lim, T. C., & Welty, C. (2017). "Effects of spatial configuration of imperviousness and green infrastructure networks on hydrologic response in a residential sewershed." *Water Resources Research*, 53(9). https://doi.org/10.1002/2017WR020631.

Limbrunner, J. F., Vogel, R. M., Chapra, S. C., & Kirshen, P. H. (2013). "Classic Optimization Techniques Applied to Stormwater and Nonpoint Source Pollution Management at the Watershed Scale." *Journal of Water Resources Planning and Management*, 139(5). https://doi.org/10.1061/(asce)wr.1943-5452.0000361.

Lin, J. (2004). "Review of published export coefficient and event mean concentration (EMC) data: ERDC TN-WRAP-04-3." Wetlands Regulatory Assistance Program. Retrieved from https://apps.dtic.mil/dtic/tr/fulltext/u2/a430436.pdf.

Link, B. G., & Phelan, J. (1995). "Social conditions as fundamental causes of disease." *Journal of Health and Social Behavior*. https://doi.org/10.2307/2626958.

Liu, L., & Jensen, M. B. (2018). "Green infrastructure for sustainable urban water management: Practices of five forerunner cities." *Cities*, 74. https://doi.org/10.1016/j.cities.2017.11.013.

Liu, Yang, Wang, C., Yu, Y., Chen, Y., Du, L., Qu, X., Peng, W., Zhang, M., & Gui, C. (2019). "Effect of urban stormwater road runoffof different land use types on an urban river in Shenzhen, China." *Water (Switzerland)*, 11(12). https://doi.org/

10.3390/w11122545.

Liu, Yaoze, Ahiablame, L. M., Bralts, V. F., & Engel, B. A. (2015). "Enhancing a rainfall-runoff model to assess the impacts of BMPs and LID practices on storm runoff." *Journal of Environmental Management*, 147. https://doi.org/10.1016/j.jenvman.2014.09.005.

Liu, Yaoze, Cibin, R., Bralts, V. F., Chaubey, I., Bowling, L. C., & Engel, B. A. (2016). "Optimal selection and placement of BMPs and LID practices with a rainfall-runoff model." *Environmental Modelling and Software*, 80. https://doi.org/10.1016/j.envsoft.2016.03.005.

Liu, Yaoze, Theller, L. O., Pijanowski, B. C., & Engel, B. A. (2016). "Optimal selection and placement of green infrastructure to reduce impacts of land use change and climate change on hydrology and water quality: An application to the Trail Creek Watershed, Indiana." *Science of the Total Environment*, 553. https://doi.org/10.1016/j.scitotenv.2016.02.116.

Liu, Yaoze, Engel, B. A., Collingsworth, P. D., & Pijanowski, B. C. (2017). "Optimal implementation of green infrastructure practices to minimize influences of land use change and climate change on hydrology and water quality: Case study in Spy Run Creek watershed, Indiana." *Science of the Total Environment*, 601–602. https://doi.org/10.1016/j.scitotenv.2017.06.015.

Loc, H. H., Duyen, P. M., Ballatore, T. J., Lan, N. H. M., & Das Gupta, A. (2017). "Applicability of sustainable urban drainage systems: An evaluation by multi-criteria analysis." *Environment Systems and Decisions*, 37(3). https://doi.org/10.1007/s10669-017-9639-4.

Loperfido, J. V., Noe, G. B., Jarnagin, S. T., & Hogan, D. M. (2014). “Effects of distributed and centralized stormwater best management practices and land cover on urban stream hydrology at the catchment scale.” *Journal of Hydrology*, 519(PC). https://doi.org/10.1016/j.jhydrol.2014.07.007.

Lottering, N., du Plessis, D., & Donaldson, R. (2015). “Coping with drought: The experience of water sensitive urban design (WSUD) in the George Municipality.” *Water SA*, 41(1). https://doi.org/10.4314/wsa.v41i1.1.

Lovell, R., Wheeler, B. W., Higgins, S. L., Irvine, K. N., & Depledge, M. H. (2014). “A Systematic Review of the Health and Well-Being Benefits of Biodiverse Environments.” *Journal of Toxicology and Environmental Health - Part B: Critical Reviews*, 17(1). https://doi.org/10.1080/10937404.2013.856361.

Luck, G. W., Smallbone, L. T., & O’Brien, R. (2009). “Socio-economics and vegetation change in urban ecosystems: Patterns in space and time.” *Ecosystems*, 12(4). https://doi.org/10.1007/s10021-009-9244-6.

Ludwig, J., Sanbonmatsu, L., Gennetian, L., Adam, E., Duncan, G. J., Katz, L. F., Kessler, R. C., Kling, J. R., Lindau, S. T., Whitaker, R. C., & McDade, T. W. (2011). “Neighborhoods, Obesity, and Diabetes — A Randomized Social Experiment.” *New England Journal of Medicine*, 365(16). https://doi.org/10.1056/nejmsa1103216.

Maas, J., van Dillen, S. M. E., Verheij, R. A., & Groenewegen, P. P. (2009). “Social contacts as a possible mechanism behind the relation between green space and health.” *Health and Place*, 15(2). https://doi.org/10.1016/j.healthplace.2008.09.006.

Macro, K., Matott, L. S., Rabideau, A., Ghodsi, S. H., & Zhu, Z. (2019). “OSTRICH-SWMM: A new multi-objective optimization tool for green infrastructure planning

with SWMM." *Environmental Modelling and Software*, 113. https://doi.org/10.1016/j.envsoft.2018.12.004.

Madureira, H., & Andresen, T. (2014). "Planning for multifunctional urban green infrastructures: Promises and challenges." *Urban Design International*, 19(1). https://doi.org/10.1057/udi.2013.11.

Mani, M., Bozorg-Haddad, O., & Loáiciga, H. A. (2019). "A new framework for the optimal management of urban runoff with low-impact development stormwater control measures considering service-performance reduction." *Journal of Hydroinformatics*, 21(5). https://doi.org/10.2166/hydro.2019.126.

Marchese, D., Reynolds, E., Bates, M. E., Morgan, H., Clark, S. S., & Linkov, I. (2018). "Resilience and sustainability: Similarities and differences in environmental management applications." *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2017.09.086.

Martikainen, P., Mäki, N., & Blomgren, J. (2004). "The effects of area and individual social characteristics on suicide risk: A multilevel study of relative contribution and effect modification." *European Journal of Population*, 20(4). https://doi.org/10.1007/s10680-004-3807-1.

Martinez, P., Blanco, M., & Castro-Campos, B. (2018). "The water-energy-food nexus: A fuzzy-cognitive mapping approach to support nexus-compliant policies in Andalusia (Spain)." *Water (Switzerland)*, 10(5). https://doi.org/10.3390/w10050664.

Mashaly, A. F., & Fernald, A. G. (2020). "Identifying capabilities and potentials of system dynamics in hydrology and water resources as a promising modeling approach for water management." *Water (Switzerland)*. https://doi.org/10.3390/w12051432.

McCabe, M. F., Rodell, M., Alsdorf, D. E., Miralles, D. G., Uijlenhoet, R., Wagner, W., Lucieer, A., Houborg, R., Verhoest, N. E. C., Franz, T. E., Shi, J., Gao, H., & Wood, E. F. (2017). "The future of Earth observation in hydrology." *Hydrology and Earth System Sciences*, 21(7). https://doi.org/10.5194/hess-21-3879-2017.

McCulloch, W. S., & Pitts, W. (1943). "A logical calculus of the ideas immanent in nervous activity." *The Bulletin of Mathematical Biophysics*, 5(4). https://doi.org/10.1007/BF02478259.

McGarity, A. E. (2012). "Storm-Water Investment Strategy Evaluation Model for Impaired Urban Watersheds." *Journal of Water Resources Planning and Management*, 138(2). https://doi.org/10.1061/(asce)wr.1943-5452.0000157.

McRae, A. M. (2016). "Case study: A conservative approach to green roof benefit quantification and valuation for public buildings." *Engineering Economist*, 61(3). https://doi.org/10.1080/0013791X.2016.1186255.

Van de Meene, S. J., Brown, R. R., & Farrelly, M. A. (2011). "Towards understanding governance for sustainable urban water management." *Global Environmental Change*, 21(3). https://doi.org/10.1016/j.gloenvcha.2011.04.003.

Meerow, S. (2019). "A green infrastructure spatial planning model for evaluating ecosystem service tradeoffs and synergies across three coastal megacities." *Environmental Research Letters*, 14(12). https://doi.org/10.1088/1748-9326/ab502c.

Meerow, S., & Newell, J. P. (2017). "Spatial planning for multifunctional green infrastructure: Growing resilience in Detroit." *Landscape and Urban Planning*, 159. https://doi.org/10.1016/j.landurbplan.2016.10.005.

Mekonnen, A. D., & Gorsevski, P. V. (2015). “A web-based participatory GIS (PGIS) for offshore wind farm suitability within Lake Erie, Ohio.” *Renewable and Sustainable Energy Reviews*. https://doi.org/10.1016/j.rser.2014.08.030.

Mhangara, P., Lamba, A., Mapurisa, W., & Mudau, N. (2019). “Towards the development of Agenda 2063 geo-portal to support sustainable development in Africa.” *ISPRS International Journal of Geo-Information*, 8(9). https://doi.org/10.3390/ijgi8090399.

Mirchi, A., Madani, K., Watkins, D., & Ahmad, S. (2012). “Synthesis of System Dynamics Tools for Holistic Conceptualization of Water Resources Problems.” *Water Resources Management*, 26(9). https://doi.org/10.1007/s11269-012-0024-2.

Mitchell, R., & Popham, F. (2008). “Effect of exposure to natural environment on health inequalities: An observational population study.” *The Lancet*, 372(9650). https://doi.org/10.1016/S0140-6736(08)61689-X.

Moon, Y. B. (2017). “Simulation modelling for sustainability: A review of the literature.” *International Journal of Sustainable Engineering*. https://doi.org/10.1080/19397038.2016.1220990.

Muleta, M. K., & Boulos, P. F. (2007). Multiobjective optimization for optimal design of urban drainage systems In *Restoring Our Natural Habitat - Proceedings of the 2007 World Environmental and Water Resources Congress*. https://doi.org/10.1061/40927(243)172.

Muscat, A., de Olde, E. M., Kovacic, Z., de Boer, I. J. M., & Ripoll-Bosch, R. (2021). “Food, energy or biomaterials? Policy coherence across agro-food and bioeconomy policy domains in the EU.” *Environmental Science and Policy*, 123. https://doi.org/10.1016/j.envsci.2021.05.001.

Nápoles, G., Espinosa, M. L., Grau, I., & Vanhoof, K. (2018). “FCM Expert: Software Tool for Scenario Analysis and Pattern Classification Based on Fuzzy Cognitive Maps.” *International Journal on Artificial Intelligence Tools*, 27(7). https://doi.org/10.1142/S0218213018600102.

Nilsson, M., Zamparutti, T., Petersen, J. E., Nykvist, B., Rudberg, P., & Mcguinn, J. (2012). “Understanding Policy Coherence: Analytical Framework and Examples of Sector-Environment Policy Interactions in the EU.” *Environmental Policy and Governance*, 22(6). https://doi.org/10.1002/eet.1589.

Nkoy, F. L., Stone, B. L., Knighton, A. J., Fassl, B. A., Johnson, J. M., Maloney, C. G., & Savitz, L. A. (2018). “Neighborhood Deprivation and Childhood Asthma Outcomes, Accounting for Insurance Coverage.” *Hospital Pediatrics*, 8(2). https://doi.org/10.1542/hpeds.2017-0032.

Nowak, D. J., Crane, D. E., & Stevens, J. C. (2006). “Air pollution removal by urban trees and shrubs in the United States.” *Urban Forestry and Urban Greening*, 4(3–4). https://doi.org/10.1016/j.ufug.2006.01.007.

O’Donnell, E. C., Lamond, J. E., & Thorne, C. R. (2017). “Recognising barriers to implementation of Blue-Green Infrastructure: A Newcastle case study.” *Urban Water Journal*, 14(9). https://doi.org/10.1080/1573062X.2017.1279190.

Olazabal, M., Chiabai, A., Foudi, S., & Neumann, M. B. (2018). “Emergence of new knowledge for climate change adaptation.” *Environmental Science and Policy*, 83. https://doi.org/10.1016/j.envsci.2018.01.017.

Oraei Zare, S., Saghafian, B., & Shamsai, A. (2012). “Multi-objective optimization for combined quality-quantity urban runoff control.” *Hydrology and Earth System Sciences*, 16(12). https://doi.org/10.5194/hess-16-4531-2012.

Osoba, O., & Kosko, B. (2019). Causal modeling with feedback fuzzy cognitive maps In *Social-Behavioral Modeling for Complex Systems*. https://doi.org/10.1002/9781119485001.ch25.

Özesmi, U., & Özesmi, S. L. (2004). “Ecological models based on people’s knowledge: A multi-step fuzzy cognitive mapping approach.” *Ecological Modelling*, 176(1–2). https://doi.org/10.1016/j.ecolmodel.2003.10.027.

Pagano, A., Pluchinotta, I., Pengal, P., Cokan, B., & Giordano, R. (2019). “Engaging stakeholders in the assessment of NBS effectiveness in flood risk reduction: A participatory System Dynamics Model for benefits and co-benefits evaluation.” *Science of the Total Environment*, 690. https://doi.org/10.1016/j.scitotenv.2019.07.059.

Pahl-Wostl, C. (2007). “The implications of complexity for integrated resources management.” *Environmental Modelling and Software*, 22(5). https://doi.org/10.1016/j.envsoft.2005.12.024.

Pande, S., & Sivapalan, M. (2017). “Progress in socio-hydrology: A meta-analysis of challenges and opportunities.” *Wiley Interdisciplinary Reviews: Water*, 4(4). https://doi.org/10.1002/wat2.1193.

Paradis, E. (2020). “A review of computer tools for prediction of ecosystems and populations: We need more open-source software.” *Environmental Modelling and Software*. https://doi.org/10.1016/j.envsoft.2020.104872.

Paterson, K. C., & Holden, N. M. (2019). “Assessment of policy conflict using systems thinking: A case study of carbon footprint reduction on Irish dairy farms.” *Environmental Science and Policy*, 101. https://doi.org/10.1016/ j.envsci.2019.07.008.

Pennino, M. J., McDonald, R. I., & Jaffe, P. R. (2016). “Watershed-scale impacts of stormwater green infrastructure on hydrology, nutrient fluxes, and combined sewer overflows in the mid-Atlantic region.” *Science of the Total Environment*, 565. https://doi.org/10.1016/ j.scitotenv.2016.05.101.

Penny, G., & Goddard, J. J. (2018). “Resilience principles in socio-hydrology: A case-study review.” *Water Security*. https://doi.org/10.1016/j.wasec.2018.11.003.

Perica, S., Pavlovic, S., Laurent, M. St., Trypaluk, C., Unruh, D., & Wilhite, O. (2018). “NOAA Atlas 14 Precipitation-Frequency Atlas of the United States Volume 11 Version 2.0: Texas.” U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service. Retrieved from https://www.weather.gov/media/owp/oh/hdsc/docs/ Atlas14_Volume11.pdf.

Perrone, A., Inam, A., Albano, R., Adamowski, J., & Sole, A. (2020). “A participatory system dynamics modeling approach to facilitate collaborative flood risk management: A case study in the Bradano River (Italy).” *Journal of Hydrology*, 580. https://doi.org/10.1016/j.jhydrol.2019.124354.

Peters-Lidard, C. D., Clark, M., Samaniego, L., Verhoest, N. E. C., Van Emmerik, T., Uijlenhoet, R., Achieng, K., Franz, T. E., & Woods, R. (2017). “Scaling, similarity, and the fourth paradigm for hydrology.” *Hydrology and Earth System Sciences*, 21(7). https://doi.org/10.5194/hess-21-3701-2017.

Pitt, R., Maestre, A., & Clary, J. (2015). "National Stormwater Quality Database (NSQD), Version 4.02 (2001-2015)." International Stormwater BMP Database. Retrieved from https://static1.squarespace.com/static/5f8dbde10268ab224c895ad7/t/5fbd4f842192d61a1f85f71a/1606242187964/NSQD_ver_4_brief_Feb_18_2018.pdf.

Planchuelo, G., von Der Lippe, M., & Kowarik, I. (2019). "Untangling the role of urban ecosystems as habitats for endangered plant species." *Landscape and Urban Planning*, 189. https://doi.org/10.1016/j.landurbplan.2019.05.007.

Pluchinotta, I., Pagano, A., Giordano, R., & Tsoukiàs, A. (2018). "A system dynamics model for supporting decision-makers in irrigation water management." *Journal of Environmental Management*, 223. https://doi.org/10.1016/j.jenvman.2018.06.083.

Puccia, C. J., & Levins, R. (1991). Qualitative Modeling in Ecology: Loop Analysis, Signed Digraphs, and Time Averaging. https://doi.org/10.1007/978-1-4613-9072-5_6.

Radinja, M., Comas, J., Corominas, L., & Atanasova, N. (2019). "Assessing stormwater control measures using modelling and a multi-criteria approach." *Journal of Environmental Management*, 243. https://doi.org/10.1016/j.jenvman.2019.04.102.

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

Rakovec, O., Kumar, R., Attinger, S., & Samaniego, L. (2016). "Improving the realism of hydrologic model functioning through multivariate parameter estimation." *Water Resources Research*, 52(10). https://doi.org/10.1002/2016WR019430.

Ramírez-Agudelo, N. A., Anento, R. P., Villares, M., & Roca, E. (2020). "Nature-based solutions for water management in peri-urban areas: Barriers and lessons learned from implementation experiences." *Sustainability (Switzerland)*. https://doi.org/10.3390/su12239799.

Ray, H., & Jakubec, S. L. (2014). "Nature-based experiences and health of cancer survivors." *Complementary Therapies in Clinical Practice*, 20(4). https://doi.org/10.1016/j.ctcp.2014.07.005.

Reed, P. M., Hadka, D., Herman, J. D., Kasprzyk, J. R., & Kollat, J. B. (2013). "Evolutionary multiobjective optimization in water resources: The past, present, and future." *Advances in Water Resources*, 51. https://doi.org/10.1016/j.advwatres.2012.01.005.

Reyes-Mendy, F., Arriagada, R. A., Reyes-Paecke, S., Bello, A., & Tobar, A. (2014). "Policy statement coherence: A methodological proposal to assess environmental public policies applied to water in Chile." *Environmental Science and Policy*, 42. https://doi.org/10.1016/j.envsci.2014.06.001.

RGME (2021). "Residential Green Infrastructure (GI) Standards for Imagination Zones." Harris County Engineering Department, Harris County Community Services Department, Houston, TX.

Richardson, G. P. (2011). "Reflections on the foundations of system dynamics." *System Dynamics Review*, 27(3). https://doi.org/10.1002/sdr.462.

Richens, R. H. (1956). "Preprogramming for mechanical translation." *Mechanical Translation*, 3(1).

Richmond, B. (1993). “Systems thinking: Critical thinking skills for the 1990s and beyond.” *System Dynamics Review*, 9(2). https://doi.org/10.1002/sdr.4260090203.

Rossi, L., Fankhauser, R., & Chèvre, N. (2006). “Water quality criteria for total suspended solids (TSS) in urban wet-weather discharges.” *Water Science and Technology*, 54(6–7). https://doi.org/10.2166/wst.2006.623.

Rossman, L. (2014). “National Stormwater Calculator User’s Guide: Version 1.1.” Environmental Protection Agency. Retrieved from https://nepis.epa.gov/Adobe/PDF/P100HD4J.pdf.

Rossman, L. A., & Huber, W. C. (2016). “Storm Water Management Model User’s Manual.” *United States Environment Protection Agency*.

Roxas, F. M. Y., Rivera, J. P. R., & Gutierrez, E. L. M. (2019). “Locating Potential Leverage Points In A Systems Thinking Causal Loop Diagram Toward Policy Intervention.” *World Futures*, 75(8). https://doi.org/10.1080/02604027.2019.1654784.

Ruangpan, L., Vojinovic, Z., Di Sabatino, S., Leo, L. S., Capobianco, V., Oen, A. M. P., Mcclain, M. E., & Lopez-Gunn, E. (2020). “Nature-based solutions for hydro-meteorological risk reduction: A state-of-the-art review of the research area.” *Natural Hazards and Earth System Sciences*, 20(1). https://doi.org/10.5194/nhess-20-243-2020.

Ruckelshaus, M. H., Guannel, G., Arkema, K., Verutes, G., Griffin, R., Guerry, A., Silver, J., Faries, J., Brenner, J., & Rosenthal, A. (2016). “Evaluating the Benefits of Green Infrastructure for Coastal Areas: Location, Location, Location.” *Coastal Management*, 44(5). https://doi.org/10.1080/08920753.2016.1208882.

Ryan, E., Pepper, M., & Munoz, A. (2021). “Causal Loop Diagram Aggregation Towards Model Completeness.” *Systemic Practice and Action Research*, 34(1). https://doi.org/10.1007/s11213-019-09507-7.

Saboohi, Y. (2001). “An evaluation of the impact of reducing energy subsidies on living expenses of households.” *Energy Policy*, 29(3). https://doi.org/10.1016/S0301-4215(00)00116-6.

Sadras, V., & Bongiovanni, R. (2004). “Use of Lorenz curves and Gini coefficients to assess yield inequality within paddocks.” *Field Crops Research*, 90(2–3). https://doi.org/10.1016/j.fcr.2004.04.003.

Santoro, S., Pluchinotta, I., Pagano, A., Pengal, P., Cokan, B., & Giordano, R. (2019). “Assessing stakeholders’ risk perception to promote Nature Based Solutions as flood protection strategies: The case of the Glinščica river (Slovenia).” *Science of the Total Environment*, 655. https://doi.org/10.1016/j.scitotenv.2018.11.116.

Sarabi, S., Han, Q., Romme, A. G. L., de Vries, B., Valkenburg, R., & den Ouden, E. (2020). “Uptake and implementation of Nature-Based Solutions: An analysis of barriers using Interpretive Structural Modeling.” *Journal of Environmental Management*, 270. https://doi.org/10.1016/j.jenvman.2020.110749.

Sarabi, S. E., Han, Q., Romme, A. G. L., de Vries, B., & Wendling, L. (2019). “Key enablers of and barriers to the uptake and implementation of nature-based solutions in urban settings: A review.” *Resources*. https://doi.org/10.3390/resources8030121.

Sarma, P. B. S., Delleur, J. W., & Rao, A. R. (1973). “Comparison of rainfall-runoff models for urban areas.” *Journal of Hydrology*, 18(3–4). https://doi.org/10.1016/0022-1694(73)90056-5.

Saysel, A. K., Barlas, Y., & Yenigün, O. (2002). “Environmental sustainability in an agricultural development project: A system dynamics approach.” *Journal of Environmental Management*, 64(3). https://doi.org/10.1006/jema.2001.0488.

Schifman, L. A., Herrmann, D. L., Shuster, W. D., Ossola, A., Garmestani, A., & Hopton, M. E. (2017). “Situating Green Infrastructure in Context: A Framework for Adaptive Socio-Hydrology in Cities.” *Water Resources Research*, 53(12). https://doi.org/10.1002/2017WR020926.

Schlossberg, M. (2003). “GIS, the US census and neighbourhood scale analysis.” *Planning Practice and Research*, 18(2–3). https://doi.org/10.1080/0269745032000168269.

Schlüter, M., & Pahl-Wostl, C. (2007). “Mechanisms of resilience in common-pool resource management systems: An agent-based model of water use in a river basin.” *Ecology and Society*, 12(2). https://doi.org/10.5751/ES-02069-120204.

Scholz, M. (2006). “Decision-support tools for sustainable drainage.” *Proceedings of the Institution of Civil Engineers: Engineering Sustainability*, 159(3). https://doi.org/10.1680/ensu.2006.159.3.117.

Scott, R. J., Cavana, R. Y., & Cameron, D. (2016). “Recent evidence on the effectiveness of group model building.” *European Journal of Operational Research*, 249(3). https://doi.org/10.1016/j.ejor.2015.06.078.

Semadeni-Davies, A., Hernebring, C., Svensson, G., & Gustafsson, L. G. (2008). “The impacts of climate change and urbanisation on drainage in Helsingborg, Sweden: Suburban stormwater.” *Journal of Hydrology*, 350(1–2). https://doi.org/10.1016/j.jhydrol.2007.11.006.

SFEI (2018). “GreenPlanIT Optimization Tool User Manual.” San Francisco Estuary Institute. Retrieved from http://greenplanit.sfei.org/sites/default/files/Optimization Tool User Manual 2020.pdf.

SFEI (2020). “GreenPlan-IT Case Study: San Jose’s Urban Villages, Chapter 3.” San Francisco Estuary Institute. Retrieved from https://greenplanit.sfei.org/books/chapter-3-case-study-san-jose’s-urban-villages.

Shahvi, S., Mellander, P. E., Jordan, P., & Fenton, O. (2021). “A Fuzzy Cognitive Map method for integrated and participatory water governance and indicators affecting drinking water supplies.” *Science of the Total Environment*, 750. https://doi.org/10.1016/j.scitotenv.2020.142193.

Singh, G. K. (2003). “Area Deprivation and Widening Inequalities in US Mortality, 1969-1998.” *American Journal of Public Health*, 93(7). https://doi.org/10.2105/AJPH.93.7.1137.

Singh, P. K., & Chudasama, H. (2020). “Evaluating poverty alleviation strategies in a developing country.” *PLoS ONE*, 15(1). https://doi.org/10.1371/journal.pone.0227176.

Sivapalan, M., & Blöschl, G. (2017). “The Growth of Hydrological Understanding: Technologies, Ideas, and Societal Needs Shape the Field.” *Water Resources Research*. https://doi.org/10.1002/2017WR021396.

Sivapalan, M., Savenije, H. H. G., & Blöschl, G. (2012). “Socio-hydrology: A new science of people and water.” *Hydrological Processes*. https://doi.org/10.1002/hyp.8426.

Soille, P., Burger, A., De Marchi, D., Kempeneers, P., Rodriguez, D., Syrris, V., & Vasilev, V. (2018). “A versatile data-intensive computing platform for information retrieval

from big geospatial data." *Future Generation Computer Systems*, 81. https://doi.org/10.1016/j.future.2017.11.007.

Solheim, A., Capobianco, V., Oen, A., Kalsnes, B., Wullf-Knutsen, T., Olsen, M., Seppia, N. Del, Arauzo, I., Balaguer, E. G., & Strout, J. M. (2021). "Implementing nature-based solutions in rural landscapes: Barriers experienced in the phusicos project." *Sustainability (Switzerland)*, 13(3). https://doi.org/10.3390/su13031461.

Song, Y., Kirkwood, N., Maksimović, Č., Zhen, X., O'Connor, D., Jin, Y., & Hou, D. (2019). "Nature based solutions for contaminated land remediation and brownfield redevelopment in cities: A review." *Science of the Total Environment*, 663. https://doi.org/10.1016/j.scitotenv.2019.01.347.

Stave, K. A. (2002). "Using system dynamics to improve public participation in environmental decisions." *System Dynamics Review*, 18(2). https://doi.org/10.1002/sdr.237.

Stepp, M. D., Winebrake, J. J., Hawker, J. S., & Skerlos, S. J. (2009). "Greenhouse gas mitigation policies and the transportation sector: The role of feedback effects on policy effectiveness." *Energy Policy*, 37(7). https://doi.org/10.1016/j.enpol.2009.03.013.

Sterman, J. D. (2001). "System dynamics modeling: Tools for learning in a complex world." *California Management Review*. https://doi.org/10.2307/41166098.

Sternam, J. D. (2002). "System Dynamics: Systems Thinking and Modeling for a Complex World." *MIT Sloan School of Management*, 147(3).

Stokols, D., Perez Lejano, R., & Hipp, J. (2013). “Enhancing the resilience of human-environment systems: A social ecological perspective.” *Ecology and Society*, 18(1). https://doi.org/10.5751/ES-05301-180107.

Storey, A., Blount, J., & Talbott, M. (2011). “Harris County low impact development & green infrastructure design criteria for storm water management.” Harris County Flood Control District & Harris County Public Infrastructure Department. Retrieved fromhttps://www.hcfcd.org/Portals/62/OurPrograms/ 2011-final_lid_gidc.pdf?ver= 2020-02-06-123158-333.

Sugumaran, R., & DeGroote, J. (2010). Spatial decision support systems: Principles and practices *Spatial Decision Support Systems: Principles and Practices*. https://doi.org/10.1201/b10322.

Sugumaran, R., Meyer, J. C., & Davis, J. (2004). “A Web-based environmental decision support system (WEDSS) for environmental planning and watershed management.” *Journal of Geographical Systems*, 6(3). https://doi.org/10.1007/s10109-004-0137-0.

Sun, T., Zhang, H., Wang, Y., Meng, X., & Wang, C. (2010). “The application of environmental Gini coefficient (EGC) in allocating wastewater discharge permit: The case study of watershed total mass control in Tianjin, China.” *Resources, Conservation and Recycling*, 54(9). https://doi.org/10.1016/j.resconrec.2009.10.017.

Sun, Z., Di, L., & Gaigalas, J. (2019). “SUIS: Simplify the use of geospatial web services in environmental modelling.” *Environmental Modelling and Software*, 119. https://doi.org/10.1016/j.envsoft.2019.06.005.

Sušnik, J., Vamvakeridou-Lyroudia, L. S., Savić, D. A., & Kapelan, Z. (2012). “Integrated System Dynamics Modelling for water scarcity assessment: Case study of the

Kairouan region." *Science of the Total Environment*, 440. https://doi.org/10.1016/j.scitotenv.2012.05.085.

Szewrański, S., Chruściński, J., van Hoof, J., Kazak, J. K., Świader, M., Tokarczyk-Dorociak, K., & Zmuda, R. (2018). "A location intelligence system for the assessment of pluvial flooding risk and the identification of stormwater pollutant sources from roads in suburbanised areas." *Water (Switzerland)*, 10(6). https://doi.org/10.3390/w10060746.

Szukalski, B. (2021). Use ArcGIS Living Atlas subscriber content in public maps and apps. Retrieved June 2, 2021, from https://www.esri.com/arcgis-blog/products/arcgis-living-atlas/mapping/living-atlas-subscriber-content-public-apps/.

Tao, T., Wang, J., Xin, K., & Li, S. (2014). "Multi-objective optimal layout of distributed storm-water detention." *International Journal of Environmental Science and Technology*, 11(5). https://doi.org/10.1007/s13762-013-0330-0.

Tayouga, S. J., & Gagné, S. A. (2016). "The socio-ecological factors that influence the adoption of green infrastructure." *Sustainability (Switzerland)*. https://doi.org/ 10.3390/su8121277.

Thorne, C. R., Lawson, E. C., Ozawa, C., Hamlin, S. L., & Smith, L. A. (2018). "Overcoming uncertainty and barriers to adoption of Blue-Green Infrastructure for urban flood risk management." *Journal of Flood Risk Management*, 11. https://doi.org/10.1111/jfr3.12218.

Tian, Y., & Huang, M. (2019). "An integrated web-based system for the monitoring and forecasting of coastal harmful algae blooms: Application to Shenzhen city, China." *Journal of Marine Science and Engineering*, 7(9).

https://doi.org/10.3390/jmse7090314.

TNRIS (2019). “Harris County LiDAR 2018.” Retrieved from https://data.tnris.org/collection/b5bd2b96-8ba5-4dc6-ba88-d88133eb6643.

Tsadiras, A. K. (2008). “Comparing the inference capabilities of binary, trivalent and sigmoid fuzzy cognitive maps.” *Information Sciences*, 178(20). https://doi.org/10.1016/j.ins.2008.05.015.

Turner, B. L., Menendez, H. M., Gates, R., Tedeschi, L. O., & Atzori, A. S. (2016). “System dynamics modeling for agricultural and natural resource management issues: Review of some past cases and forecasting future roles.” *Resources*. https://doi.org/10.3390/resources5040040.

Tzoulas, K., Korpela, K., Venn, S., Yli-Pelkonen, V., Kaźmierczak, A., Niemela, J., & James, P. (2007). “Promoting ecosystem and human health in urban areas using Green Infrastructure: A literature review.” *Landscape and Urban Planning*. https://doi.org/10.1016/j.landurbplan.2007.02.001.

UN Environment Programme (2019). “Nature-based solutions for climate manifesto.” Retrieved from https://Www.Unenvironment.Org/Nature-Based-Solutions-Climate.

UNEP (2019). “The UN Environment Programme and nature-based solutions.” United Nations Environment Programme. Retrieved from https://www.unep.org/unga/our-position/unep-and-nature-based-solutions.

UNISDR, & CRED (2015). “The human cost of weather-related disasters 1995-2015.” *UNISDR Publications* (Vol. 1).

United Nations (2018). “World Urbanization Prospects 2018.” *Department of Economic and Social Affairs. World Population Prospects 2018.*

University of Wisconsin School of Medicine and Public (2019). “Area Deprivation Index.” Retrieved from https://www.neighborhoodatlas.medicine.wisc.edu.

USDA (1986). “Urban Hydrology for Small Watersheds: TR-55.” United States Department of Agriculture, Natural Resources Conservation Service, Conservation Enginereing Division. Retrieved from https://www.nrcs.usda.gov/Internet/ FSE_DOCUMENTS/ stelprdb1044171.pdf.

USGS (2021a). “USGS 08074020 Whiteoak Bayou at Alabonson Rd, Houston, TX.” United States Geological Survey. Retrieved from https://waterdata.usgs.gov/tx/ nwis/uv/?site_no=08074020&PARAmeter_cd=00065,00060.

USGS (2021b). “USGS 08074500 Whiteoak Bayou at Houston, TX.” United States Geological Survey. Retrieved from https://waterdata.usgs.gov/tx/nwis/uv/ ?site_no=08074500&PARAmeter_cd=00065,00060.

Vacca, G., Fiorino, D. R., & Pili, D. (2018). “A spatial information system (sis) for the architectural and cultural heritage of sardinia (Italy).” *ISPRS International Journal of Geo-Information*, 7(2). https://doi.org/10.3390/ijgi7020049.

Vandermeulen, V., Verspecht, A., Vermeire, B., Van Huylenbroeck, G., & Gellynck, X. (2011). “The use of economic valuation to create public support for green infrastructure investments in urban areas.” *Landscape and Urban Planning*, 103(2). https://doi.org/10.1016/j.landurbplan.2011.07.010.

Vásquez, A., Devoto, C., Giannotti, E., & Velásquez, P. (2016). Green Infrastructure Systems Facing Fragmented Cities in Latin America - Case of Santiago, Chile In *Procedia Engineering* (Vol. 161). https://doi.org/10.1016/j.proeng.2016.08.602.

Veenendaal, B., Brovelli, M. A., & Li, S. (2017). “Review of web mapping: Eras, trends and directions.” *ISPRS International Journal of Geo-Information*. https://doi.org/10.3390/ijgi6100317.

Vennix, J. A. M. (1999). “Group model-building: Tackling messy problems.” *System Dynamics Review*, 15(4). https://doi.org/10.1002/(SICI)1099-1727(199924)15:4<379::AID-SDR179>3.0.CO;2-E.

Vitolo, C., Elkhatib, Y., Reusser, D., Macleod, C. J. A., & Buytaert, W. (2015). “Web technologies for environmental Big Data.” *Environmental Modelling and Software*. https://doi.org/10.1016/j.envsoft.2014.10.007.

Vogel, J. R., Moore, T. L., Coffman, R. R., Rodie, S. N., Hutchinson, S. L., McDonough, K. R., McLemore, A. J., & McMaine, J. T. (2015). “Critical Review of Technical Questions Facing Low Impact Development and Green Infrastructure: A Perspective from the Great Plains.” *Water Environment Research*, 87(9). https://doi.org/10.2175/106143015x14362865226392.

Vörösmarty, C. J., Pahl-Wostl, C., Bunn, S. E., & Lawford, R. (2013). “Global water, the anthropocene and the transformation of a science.” *Current Opinion in Environmental Sustainability*. https://doi.org/10.1016/j.cosust.2013.10.005.

de Vries, S., Verheij, R. A., Groenewegen, P. P., & Spreeuwenberg, P. (2003). “Natural environments - Healthy environments? An exploratory analysis of the relationship between greenspace and health.” *Environment and Planning A*, 35(10). https://doi.org/10.1068/a35111.

Vugteveen, P., Rouwette, E., Stouten, H., van Katwijk, M. M., & Hanssen, L. (2015). “Developing social-ecological system indicators using group model building.” *Ocean*

and Coastal Management, 109. https://doi.org/10.1016/j.ocecoaman.2015.02.011.

Wamsler, C., Wickenberg, B., Hanson, H., Alkan Olsson, J., Stålhammar, S., Björn, H., Falck, H., Gerell, D., Oskarsson, T., Simonsson, E., Torffvit, F., & Zelmerlow, F. (2020). "Environmental and climate policy integration: Targeted strategies for overcoming barriers to nature-based solutions and climate change adaptation." *Journal of Cleaner Production*, 247. https://doi.org/10.1016/j.jclepro.2019.119154.

White, M., Harmel, D., Yen, H., Arnold, J., Gambone, M., & Haney, R. (2015). "Development of Sediment and Nutrient Export Coefficients for U.S. Ecoregions." *Journal of the American Water Resources Association*, 51(3). https://doi.org/10.1111/jawr.12270.

White, T. J. (2007). "Sharing resources: The global distribution of the Ecological Footprint." *Ecological Economics*, 64(2). https://doi.org/10.1016/j.ecolecon.2007.07.024.

Wihlborg, M., Sörensen, J., & Alkan Olsson, J. (2019). "Assessment of barriers and drivers for implementation of blue-green solutions in Swedish municipalities." *Journal of Environmental Management*, 233. https://doi.org/10.1016/j.jenvman.2018.12.018.

Winz, I., Brierley, G., & Trowsdale, S. (2009). "The use of system dynamics simulation in water resources management." *Water Resources Management*, 23(7). https://doi.org/10.1007/s11269-008-9328-7.

Working Group on Planning (GTplan) (2013). "Spatial Data Infrastructure (SDI) Manual for the Americas." *Report of the Permanent Committee for Geospatial Data Infrastructure of the Americas Spatial*.

Wu, J., Kauhanen, P. G., Hunt, J. A., Senn, D. B., Hale, T., & McKee, L. J. (2019). "Optimal Selection and Placement of Green Infrastructure in Urban Watersheds for PCB Control." *Journal of Sustainable Water in the Built Environment*, 5(2). https://doi.org/10.1061/jswbay.0000876.

Yan, D., Jia, Z., Xue, J., Sun, H., Gui, D., Liu, Y., & Zeng, X. (2018). "Inter-regional coordination to improve equality in the agricultural virtualwater trade." *Sustainability (Switzerland)*, 10(12). https://doi.org/10.3390/su10124561.

Yang, L., Jin, S., Danielson, P., Homer, C., Gass, L., Bender, S. M., Case, A., Costello, C., Dewitz, J., Fry, J., Funk, M., Granneman, B., Liknes, G. C., Rigge, M., & Xian, G. (2018). "A new generation of the United States National Land Cover Database: Requirements, research priorities, design, and implementation strategies." *ISPRS Journal of Photogrammetry and Remote Sensing*, 146. https://doi.org/10.1016/j.isprsjprs.2018.09.006.

Zadeh, L. A. (1975). "The concept of a linguistic variable and its application to approximate reasoning-I." *Information Sciences*, 8(3). https://doi.org/10.1016/0020-0255(75)90036-5.

Zare, F., Elsawah, S., Bagheri, A., Nabavi, E., & Jakeman, A. J. (2019). "Improved integrated water resource modelling by combining DPSIR and system dynamics conceptual modelling techniques." *Journal of Environmental Management*, 246. https://doi.org/10.1016/j.jenvman.2019.05.033.

Zellner, M., Massey, D., Minor, E., & Gonzalez-Meler, M. (2016). “Exploring the effects of green infrastructure placement on neighborhood-level flooding via spatially explicit simulations.” *Computers, Environment and Urban Systems*, 59. https://doi.org/10.1016/j.compenvurbsys.2016.04.008.

Zhang, C., Di, L., Sun, Z., Lin, L., Yu, E. G., & Gaigalas, J. (2019). “Exploring cloud-based Web Processing Service: A case study on the implementation of CMAQ as a Service.” *Environmental Modelling and Software*, 113. https://doi.org/10.1016/j.envsoft.2018.11.019.

Zhang, D., Shen, J., Liu, P., Zhang, Q., & Sun, F. (2020). “Use of fuzzy analytic hierarchy process and environmental gini coefficient for allocation of regional flood drainage rights.” *International Journal of Environmental Research and Public Health*, 17(6). https://doi.org/10.3390/ijerph17062063.

Zhang, G., Hamlett, J. M., Reed, P., & Tang, Y. (2013). “Multi-Objective Optimization of Low Impact Development Designs in an Urbanizing Watershed.” *Open Journal of Optimization*, 02(04). https://doi.org/10.4236/ojop.2013.24013.

Zhang, K., & Chui, T. F. M. (2018). “A comprehensive review of spatial allocation of LID-BMP-GI practices: Strategies and optimization tools.” *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2017.11.281.

Zhang, M., Jiang, L., Yue, P., & Gong, J. (2020). “Interoperable web sharing of environmental models using OGC web processing service and Open Modeling Interface (OpenMI).” *Environmental Modelling and Software*, 133. https://doi.org/10.1016/j.envsoft.2020.104838.

Zhou, W., Chi, C. H., Wang, C., Wong, R., & Ding, C. (2014). Bridging the gap between spatial data sources and mashup applications In *Proceedings - 2014 IEEE International Congress on Big Data, BigData Congress 2014*. https://doi.org/10.1109/BigData.Congress.2014.86.

Zomorodian, M., Lai, S. H., Homayounfar, M., Ibrahim, S., Fatemi, S. E., & El-Shafie, A. (2018). "The state-of-the-art system dynamics application in integrated water resources modeling." *Journal of Environmental Management*. https://doi.org/10.1016/j.jenvman.2018.08.097.

Zuniga-Teran, A. A., Staddon, C., de Vito, L., Gerlak, A. K., Ward, S., Schoeman, Y., Hart, A., & Booth, G. (2020). "Challenges of mainstreaming green infrastructure in built environment professions." *Journal of Environmental Planning and Management*, 63(4). https://doi.org/10.1080/09640568.2019.1605890.

APPENDICES

Appendix A. Scripts for group modeling building of a causal loop diagram.

Script 1: Logistics and Room Set Up

This script is used to create an inviting and conducive environment for group model-building (GMB) participants before the GMB session begins.

Status: Best practices

Primary nature of group task: Offline

Time

- Preparation time: 30 minutes
- Time required during session: 0 minutes
- Follow-up time: 0 minutes

Materials: The materials needed for group model building session

Inputs: A discussion for how the room should be set up.

Outputs: A plan for room set-up [Zoom].

Roles: Facilitators experienced in GMB and the design of the workshop.

Steps

1. Arrange the table, chairs, and flip charts in the room in a manner conducive to upcoming activities and scripts. Consider how participants should be sitting.
2. In a semicircle facing either the wall where a model is projected, the white board, or the chalkboard.
3. In clusters of tables so participants can work in small groups. [N/A] Pre-built Zoom Whiteboard template for Variable Elicitation script.
4. Arrange power cords, tables, and chairs for members not sitting at the table with participants (e.g., recorders, modelers, coaches).
5. Secure any power cords and extension cables with tape to minimize the risk that people may trip.[N/A] Enable Zoom Whiteboard for variable elicitation.
    - Virtual Sticky Notes
    - Virtual Text Boxes
    - Export Image (PNG) of Whiteboard periodically during group-building.
6. Arrange refreshments in a place that is convenient for participants to get up and access during the session. [Include several virtual breaks during workshop.]

Evaluation Criteria: Thoughtful room set-up that will contribute to participants' comfort, engagement, and understanding.

Authors: Andersen and Richardson

History: Documented by Annaliese Calhoun in 2010 based on Luna-Reyes et al. (2006).

Revisions: Peter Hovmand (2013) to provide more details on room arrangements.

References: Luna-Reyes, L. F., Martinez-Moyano, I. J., Pardo, T. A., Cresswell, A. M., Andersen, D. F., & Richardson, G. P. (2006). Anatomy of a group model-building intervention: Building dynamic theory from case study research. *System Dynamics Review*, 22(4), 291-320.

Notes: Successful GMB sessions require the qualities and comfort of the physical facilities and the smooth handling of logistics for the sessions. This should include removing the participants from their phones and work site and providing a relaxing change from routine work. Multi-day sessions should be located and planned to provide high-quality lodging, meals, and opportunities for social interaction.

Script 2: Chickens and Eggs Example

This script is used to introduce concepts of causal loop diagram (CLD) and provide an example of feedback loops.to those without knowledge of system dynamics. The purpose of the script is to provide a universal and easy to understand metaphor for complex systems.

Status: Promising

Primary nature of group task: Presentation

Time

- Preparation time: 5 minutes
- Time required during session: 10 minutes
- Follow-up time: 0 minutes

Materials

- Markers or pens.
- A white board or flip chart papers.

Inputs

- A story of chickens' reproduction, growth, overcrowding, and injuries.
- A graph over time of chicken population growth dynamic.
- A drawing with chicken crossing roads if preferred.

Outputs

- A causal loop diagram of chicken population growth dynamic with variables, polarity, feedback loops, and delays.
- Familiarity with the concepts of feedback loops (reinforcing and balancing), causal relationships with polarities between variables, and how to interpret dynamics from a causal loop diagram.

Roles: Modeler with training in system dynamics or community-based system dynamics.

Steps

1. First, the facilitator will tell a story of chickens reproducing, population growth, overcrowding, and injuries, while drawing a picture of the narrative.
2. Then, the facilitator will present a graph over time to describe this dynamic – of chicken population growth with a hope of sustained growth, and a fear of collapse.
3. The facilitator then draws a causal loop diagram to represent the reinforcing and balancing loops of the story. The facilitator then explains that the model functions as a "dynamic hypothesis" of the structure that may create this behavior.

   The presentation should highlight:

   - Polarity,
   - What a variable means (it varies)
   - Feedback loops (reinforcing and balancing)
   - Delays
4. (S)he then asks if there are other factors or structures, and can add on other sources of injuries, other factors that reduce eggs, etc. and maps those factors onto the CLD, to demonstrate that models are meant to be tools for dialogue and thinking. As participants nominate additional links, the facilitator adds those links to the model.

Evaluation Criteria: Participants contribute variables indicating understanding of dynamic variables.

Authors: Originally developed by Brian Biroscek. Refined and expanded by Peter Hovmand, Ellis Ballard and the Social System Design Lab.

Script 3: Variable Elicitation

This script is used to facilitate consensus-based group discussion about the model problem and boundaries early in the modeling process.

Status: Best practices

Primary nature of group task: Divergent

Time

- Time required during session: 20 minutes
- Follow-up time: 0 minutes

Materials

- Markers or pens and paper.
- A white board or flip chart papers.

Inputs: None [Keep list of variables from literature review to the side of the screen for group guidance during live-session, if necessary.]

Outputs: Prioritized list of variables.

Roles

- Facilitator with moderate expertise in SD and small group facilitation.
- Wall builder with moderate expertise in SD.
- Runner (optional) to transfer variables from facilitator to wall builder.

Steps

1. The facilitator gives each participant sheets of blank paper and markers. [Introduce virtual Whiteboard with blank, colored boxes and titles of each theme to be considered].
2. The facilitator writes a task-focusing question such as, "What are the key variables affecting the process and outcomes of the [project name] project?" on the whiteboard.
3. The facilitator asks participants to write as many problem-related variables as they can on the sheets of paper. Each variable should be listed on its own sheet of paper. Participants are given a few minutes to work individually on their lists.
4. Once the participants have finished the individual exercise, the facilitator has the participants share their variables one at a time in a round-robin fashion similar to the process used in the "Hopes and Fears" script. When a variable name is open to several interpretations, the facilitator asks for a brief description or definition of the variable, including the units in which the variable can be measured.
5. The facilitator (or runner) hands each variable to the wall builder, who tapes them on the wall in thematic clusters.
6. Once all of the variables have been shared, the wall builder reflects back the themes that emerged from wall-building and asks participants for feedback. The wall builder may ask questions such as "Does this resonate with you? Are there other themes you notice, or any variables you think should be moved?"
7. Optionally, the facilitator asks the participants to prioritize the variables by simple voting mechanisms. Individuals can vote for as many variables as they want. The number of votes for each variable is also written down on the board.
8. The facilitator makes a summary of the variables on the board, while the recorder captures the products of the process either photographically or in a word processor.
9. The facilitator suggests which variables can be considered stocks as they are mentioned. If the participants agree, the facilitator can add the words "level of" to these variables.

Evaluation Criteria: Identification of key variables and stocks.

Authors: Andersen and Richardson

History: Originally described in Luna-Reyes et al. (2006).

References: Luna-Reyes, L. F., Martinez-Moyano, I. J., Pardo, T. A., Cresswell, A. M., Andersen, D. F., & Richardson, G. P. (2006). Anatomy of a group model-building intervention: Building dynamic theory from case study research. *System Dynamics Review*, 22(4), 291-320.

Notes: A variation of this script is the Nominal Group Technique. Based on group size, decide whether to break participants into subgroups. In smaller groups (N<10), allow individuals to work and present independently. In larger groups (N >10), divide participants into subgroups of roughly 10. Ask the subgroups to sit together.

Script 4: Causal Mapping with Seed Structure

This script is used to elicit causal structures at the beginning of a group model building process when there is an interest in quickly illustrating how a focal problem or situation could involve a system of interacting feedback loops.

Status: Best practices

Primary nature of group task: Divergent

Time

- Preparation time: 180 minutes
- Time required during session: 90 minutes
- Follow-up time: 90 minutes

Materials

- Data projector
- Computer running modeling software (e.g., Vensim)
- Recorder's materials
- Flip charts with key words posted in the room

Inputs: Stock-flow seed structure from prior work with core modeling team.

Outputs: Causal map of reinforcing and balancing feedback loops that identify variables and structures related to a focal problem.

Roles

- Modeler with expertise in system dynamics modeling who can draw diagrams in real time.
- Facilitator familiar with the situation and language used by participants to discuss the problem, and strong group facilitation skills appropriate to the culture of participation.
- Recorder with some exposure to system dynamics and/or familiarity with the context of the issue.

Steps

1. The modeler, who is sitting with a laptop connected to a data projector, and the facilitator are at the front of the room. The modeler could also be drawing the structure by hand on a white board or paper, as long as it is visible to the entire group.
2. The facilitator begins by explaining, "We're going to spend the next 90 minutes or so doing a causal mapping exercise [on the previously identified issue]."
3. The modeler explains that the diagram that will result from this will be available to them. The modeler then introduces the seed structure with the stock and flows.
4. If changes are suggested or needed, the facilitator affirms the changes while the modeler captures the changes.
5. The facilitator then explains that participants can talk about their own experience or what they see in their family or community.
6. The recorders document working definitions used for key words.
7. The facilitator then asks questions that help identify impact and causal relations between identified key variables.
8. As someone suggests something, the modeler draws the link on the model in front of the room. The facilitator and modeler will then encourage participants to add variables and relationships. The modeler tries to get things recorded using exactly the same terms as the participants.
9. Meanwhile, the recorders are taking notes on the variables named, relationships being described, and quotes or stories that help put some context around the story. If necessary, the recorder uses the number chart developed earlier to help identify who is saying what.
10. The modeler explains the notation as the structure is drawn on the board. This includes arrows, polarity ('+', '-'), and feedback loops as they appear in the diagram.
11. The recorders write down relationships and should, as much as possible, use arrows in causal chains with '+' and '–' signs to indicate the direction of the relationship. A '+' sign indicates that increasing one leads to an increase in the other, and a decrease in one leads to a decrease in the other. A '-' sign indicates an opposite effect where increasing one leads to a decrease in the other, and a decrease in one leads to an increase in the other.

12. The recorders should avoid interrupting the flow of the conversation between participants and generally avoid asking clarifying questions or adding comments. They should simply make a note of the questions or comments in the margins and distinguish them from things that participants said, such as by using an asterisk (*) symbol.
13. The modeler will interject when the first feedback loop has been formed.
14. If the group begins to slow down and there is time, or no feedback loop has been formed, the modeler will ask if there are any relationships between the identified variables that have not been discussed. Doing this will help create loops that might otherwise have been missed.
15. The process continues until there are about 5 minutes left in the exercise, at which point the modeler points out, "We've only spent a little time, less than 90 minutes, coming up with some of these relationships and already it is looking pretty complicated." However, this is still much simpler than the reality they are trying to manage in practice and research. Ask if there are any other important variables or relationships that haven't been described.

Evaluation Criteria

- Energized participants interested in more modeling
- A causal map with multiple feedback loops
- Recognizing that there is a feedback system producing the reported behavior

Authors: Unknown

History: This particular script was first based on an activity conducted with Save the Children UK, Mongolia in 2006 and was formalized as part of the Missouri Transformation Project. Lune-Reyes et al. (2006) describes a similar activity.

Revisions: Revised 2013 by Peter Hovmand to reflect current practices.

References: Luna-Reyes, L. F., Martinez-Moyano, I. J., Pardo, T. A., Cresswell, A. M., Andersen, D. F., & Richardson, G. P. (2006). Anatomy of a group model-building intervention: Building dynamic theory from case study research. *System Dynamics Review*.

Notes: This exercise is based on a more general, common activity in system dynamics modeling that follows from using system dynamics modeling software in classrooms, workshops, and group model building. The exercise works well for quickly (1) conveying the idea that systems are complex, (2) introducing the language of system dynamics (e.g., balancing and reinforcing feedback loops, stocks and flows), and (3) grounding the emerging model in participants' language. The exercise can be conducted with large groups up to about 50 or 60 individuals, but participation tends to be limited after the group size exceeds 20 individuals. The design of the seed structure is critical and should be piloted before attempting to conduct this exercise.

Script 5: Creating Causal Loop Diagram from Variable List

This can be used to introduce causal loop diagramming after a list of variables have been identified (e.g., from a variable elicitation, connection circle, or graphs over time exercise).

Status: Promising practice

Primary nature of group task: Convergent

Time

- Preparation time: 10 minutes
- Time required during session: 40 minutes
- Follow-up time: 15 minutes

Materials

- Flip chart paper for each group or large whiteboard/chalkboard.
- Markers.

Inputs: List of variables (e.g., from variable elicitation, connection circle exercise, or graphs over time).

Outputs: Set of causal loop diagram.

Roles: Modeler/facilitator with experience drawing causal loop diagrams and comfortable introducing conventions.

Steps

1. Introduce the exercise by reviewing the variable list.
2. Either in the same groupings or new groupings, instruct the teams to now construct a causal loop diagram based on the connection circles. Sample instructions:

We're now going to create a causal loop diagram identifying hypothesized causal relationships between variables. These connections can be based on the literature, your own research or conjectures.

To do this, begin by picking variables that are important and transferring them to [your sheet of paper/the whiteboard] and then drawing a casual arrow from the cause to the effect. Then add a plus or minus sign to indicate the direction of influence with plus signs representing change in the same direction or positive associations, and minus signs representing change in the opposite direction or negative associations. If you can't decide if a link should be plus or minus, and this is because you're not sure as a group, use a question mark. If it could be both, then draw two separate causal links, one positive and one negative.

As the number of links increases, look for positive and reinforcing feedback loops.

For example, as education increases, income increases, and as income increases, there are more opportunities for even more education. This represents a reinforcing loop because the direction of change is reinforced. This same loop can either be a virtuous cycle or vicious cycle. For example, if I lose my job and income decreases, it may limit my ability to get an

education, which in turn may make it even hard to get a job or future promotion, and this in turn would lower my income (draw the CLD shown in Figure 1).

Of course, this can't go on forever (either in the vicious or the virtuous cycle). As I go to school and get more education, the hours per week that I can work decreases, which in turn leads to less income (draw the balancing loop so that the CLD matches what is shown in Figure 2). Notice that less hours per week leads to less income. The converse is also true, more hours per week leads to more income. This is what kind of link, plus or minus? Answer: plus, correct. However, now with less income, there is also a limit on education. This forms a balancing loop: as I increase education, my hours per week decreases, leading to less income, which then leads to a decrease in education. I started with an increase education and ended up with a decrease in education, hence the behavior of this outer loop counteracts or balances the initial direction of change.

Our goal in this exercise is to develop a causal loop diagram, meaning we're looking to identify the individual linkages between variables as well as the loops. So, a good strategy here is to look for ways to "close the loop". We do this by looking for variables that don't have any arrows going into them and seeing if there is another variable in our model that might influence this variable. If there is, we can then draw a link.

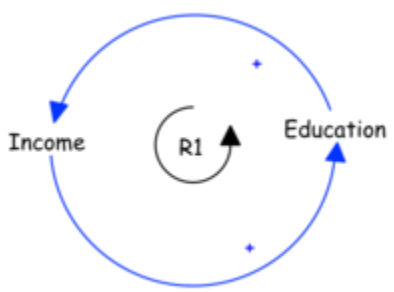

Figure A.1. Single reinforcing loop (R1)

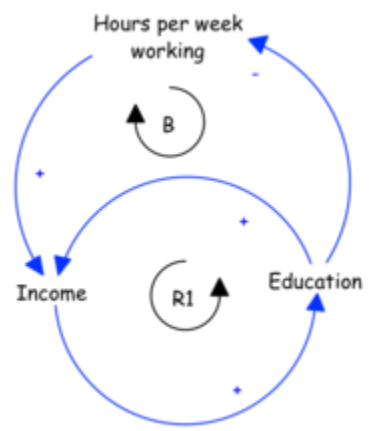

Figure A.2. Reinforcing loop R1 with the addition of a balancing loop (B1)

3. As groups work on their causal loop diagrams, facilitators walk around the room, observe how the groups are doing, and coach them. Consider the focus of coaching in three phases:
    - (Beginning, first 5 minutes): focus on clarifying the instructions and provide positive reinforcement that they are on the right track. For example: "That looks great. You have several variables representing [topic] and causal links with polarities identified."
    - (Middle): Focus on helping groups improve their skills in developing the diagrams and representing their discussion. For example: "Remember, if you want to show a relationship that goes in both directions, draw two separate lines," or "Seems like you're having a lot of disagreement about whether the variable is the same for all communities. Why don't you try

adding a second variable and representing both ideas on the page, even if they feel a bit contradictory, or only relevant for some communities."

- (End, last 5 minutes): look for a group that has a good example to start the next exercise, and role model how one explains the connections: "You have 5 minutes left before we return to large group," or "That looks great. I see how [variable 1] is influencing [variable 2], and this is influencing [variable 3], which then affects [variable 4]. You also have a couple of feedback loops. This one is reinforcing (point to loop and talk it through) and this one is balancing (point to loop and talk it through). Nice job!"

4. Tell the groups to stop after 15 minutes and ask each group to present their connection circles.
    - What were some of the main themes your group ended up discussing?
    - Where did you see the most interesting feedback loops?

Evaluation Criteria: Participants created a rich causal loop diagram (CLD) based on their thoughts and stories.

Authors: Peter Hovmand 2017

History: This was originally based on the Hovmand and Kraus (2013) "Creating Causal Loop Diagram from Connection Circles" script as part of Raising St. Louis in 2013 where the connection circle exercise provided a "warm up" for a group and an initial set of associations for the CLD. This was found to be helpful for groups that tended to feel more comfortable in correlational thinking and the barrier too steep for jumping directly into operational thinking from the feedback perspective. However, relying on the connection circles as a starting point often meant that the group did not get a sense to develop a shared view of the dynamics of the system as might be typical through the graphs over time exercise. Although going from a graphs over time to connection circle exercise, and then from the connection circle exercise to a causal loop diagram might have been an option, it seemed that one might be able to go directly from graphs over time to causal loop diagramming with some groups. Hence, the basis for this script.

Script 6: Model Review

This script is used to summarize dynamic insights and stories, clarify fuzzy ideas, capture additional information about model structure, and elicit feedback from participants after causal structures have been developed, typically at the end of a session.

Status: Best practices

Primary nature of group task: Convergent

Time

- Preparation time: 5 minutes
- Time required during session: 15 minutes

Materials: Screen/whiteboard

Inputs: Diagram of model.

Outputs

- List of main feedback loops and dynamics identified.
- List of insights gained from the connection circle exercise.

Roles

- Modeler with experience building models.
- Reflector with experience building and analyzing system dynamics models.
- Recorder with note-taking experience.

Steps

1. At the start of the model review, the modeler moves up to the front of the room.
2. The modeler describes the causal loop diagram and stresses that this is another reflection of the exact same linkages and variables discussed during the exercise and that none of these elements have been changed. Modeler notes that plus and minus signs mean the same as in the previous exercise.
3. In a causal diagram, the modeler takes care to explain reinforcing and balancing loops by tracing examples within the model (if available). Modeler introduces the reflector so that the reflector can discuss more insights regarding feedback within the model.
4. The reflector reviews key insights from the causal map and reads back the stories associated with major reinforcing and balancing feedback loops, intervention points, etc.
5. After the reflector has reviewed the diagram, the reflector then initiates questioning regarding what didn't get recaptured or is missing from the diagram. The reflector assesses confirmation of the adequacy of the diagram as a representation of the group thinking. The recorders document the insights shared.
6. The reflector also will point out subsequent, important changes in structure, help the group identify what is happening with the modeling, and highlight model-based insights that emerge.

Evaluation Criteria

- A revised causal loop diagram that is based on an initial discussion.
- A shared understanding of the changes in the model and insights that have emerged.

History: Based on the original script "Causal Mapping from Discussion" by Peter Hovmand, created on April 19, 2010.

Revisions: Revised May 22, 2012 by Alison Kraus and Peter Hovmand. Revised March 4, 2012 by Meagan Colvin and Peter Hovmand.

References: Richardson, G. P. (1997). Problems in causal loop diagrams. *System Dynamics Review, 13*(3), 247-25

Appendix B. 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

Appendix B (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

Appendix B (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

Appendix B (continued):

			No. Possible NBS Features		
Subcatchment No.	**Area (AC)**	**Impervious Cover (%)**	**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

Appendix B (continued):

			No. Possible NBS Features		
Subcatchment No.	**Area (AC)**	**Impervious Cover (%)**	**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