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Systems-thinking for environmental policy coherence: Stakeholder knowledge, fuzzy logic, and causal reasoning

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ABSTRACT

Environmental policies are often chosen according to physical characteristics that disregard the complex interactions between decision-makers, society, and nature. Environmental policy resistance has been identified as stemming from such complexities, yet we lack an understanding of how social and physical factors interrelate to inform policy design. The identification of synergies and trade-offs among various management strategies is necessary to generate optimal results from limited institutional resources. Participatory modeling has been used within the environmental community to aid decision-making by bringing together diverse stakeholders and defining their shared understanding of complex systems, which are commonly depicted by causal feedbacks. While such approaches have increased awareness of system complexity, causal diagrams often result in numerous feedback loops that are difficult to disentangle without further, data-intensive modeling. When investigating the complexities of human decision-making, we often lack robust empirical datasets to quantify human behavior and environmental feedbacks. Fuzzy logic may be used to convert qualitative relationships into semi-quantitative representations for numerical simulation. However, sole reliance upon computer-simulated outputs may obscure our understanding of the underlying system dynamics. Therefore, the aim of this study is to present and demonstrate a mixed-methods approach for better understanding: 1) *how* the system will respond to unique management strategies, in terms of policy synergies and conflicts, and 2) *why* the system behaves as such, according to causal feedbacks embedded within the system dynamics. This framework is demonstrated through a case study of nature-based solutions and policymaking in Houston, Texas, USA.

1. Introduction

Environmental problems and their solutions are complex in nature and are often challenged by social and institutional constructs that are not well-understood. Policymakers strive to make decisions that produce maximum benefits while minimizing adverse consequences, which requires identifying and connecting all possible outcomes that could produce synergies and trade-offs between components. In complex systems, such interactions may produce emergent behavior, where a shift in one component triggers self-regulating and/or divergent outcomes elsewhere. When human actors interact with the environment through planning and group behavior, social and political constructs adapt to the new setting, which further refines local values and drives emergent phenomena. Each cycle of this dynamic system denotes a new human-nature response, which must be assessed according to altered characteristics. When confronted with a system of many parts, humans may try to rationalize the problem by focusing on select connections, thereby misperceiving the overall system structure and behavior. This inability to identify complex system dynamics often results in missed opportunities and/or unintended outcomes from well-meaning interventions, a phenomenon known as "policy resistance" (Sterman, 2001).

> *"Policy resistance occurs when policy actions trigger feedback from the environment that undermines the policy and at times even exacerbates the original problem,"* (Ghaffarzadegan et al., 2011).

Therefore, we cannot mitigate environmental issues by simply assigning policies that resolve select barriers and assume the results will be proportionally related to the change. 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. The means

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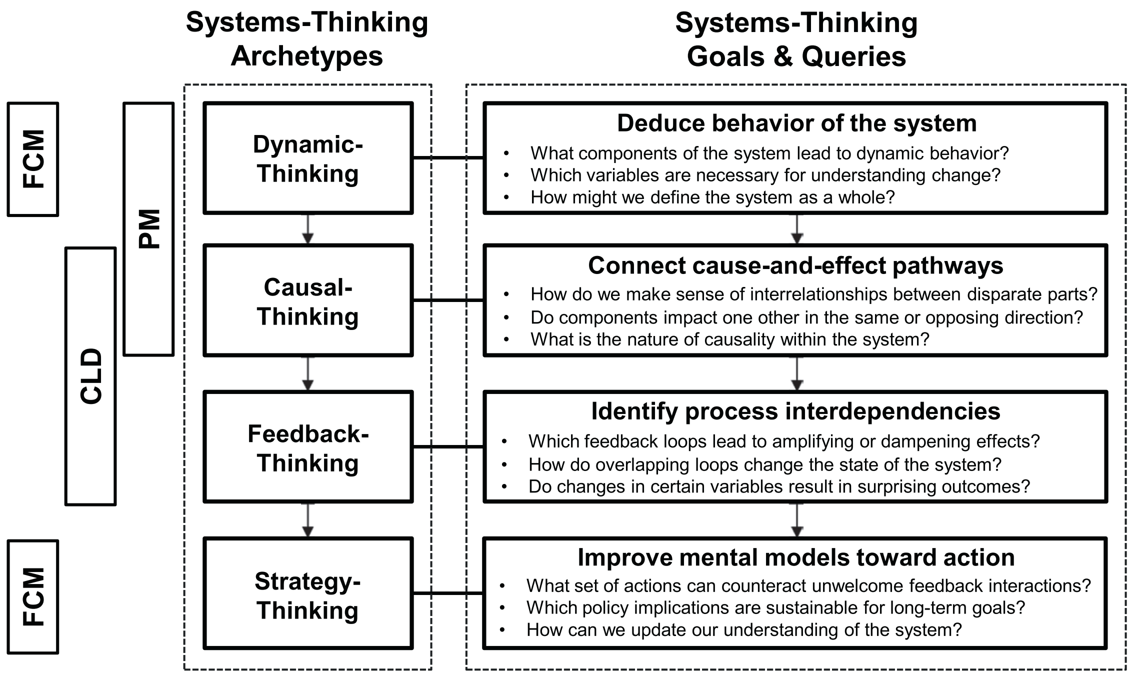

Fig. 1. General framework of how a holistic application of systems-thinking can be used to define complex, dynamic systems and assess policy effectiveness for a set of management strategies. The boxes on the left represent the common systems-thinking processes included within each of the primary archetypes (PM = participatory modeling, CLD = causal loop diagramming, FCM = fuzzy-cognitive mapping).

for circumventing policy resistance is to transition the planning paradigm from a reductionist worldview toward a greater awareness of and appreciation for system complexity (Roxas et al., 2019). In the case of environmental management, system complexity arises from the coupling between human behavior (e.g., policy interventions, community activism, shifts in perception) and environmental responses (e.g., ecosystem performance, conservation/restoration activities). When such dimensions are integrated holistically to produce optimal results, the system is said to have achieved "policy coherence".

> *"Policy coherence for development means, as a first definition, the absence of incoherences, which occur when other policies deliberately or accidentally impair the effects of development policy or run counter to its intentions. A second, more ambitious definition sees policy coherence as the interaction of all policies that are relevant in the given context with a view to the achievement of overriding development objectives,"* (Ashoff, 2005).

In other words, policy coherence describes the extent to which a given policy (or set of policies) imposed on a system result in optimal interactions between the system sub-components. While the literature is not consistent in defining and measuring policy coherence, a general understanding is that coherence is achieved when interventions trigger more policy synergies than conflicts. *Policy synergy* is a term used to describe how management strategies interact as a cohesive unit to accomplish more than the sum of their parts. 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 policy objectives. Conversely, *policy conflict* occurs when unique strategies interact to produce worse outcomes, or trade-offs, than had each intervention been implemented in silo (Muscat et al., 2021; Nilsson et al., 2012; Reyes-Mendy et al., 2014). In other words, policy coherence helps us identify the extent to which unique management strategies are either reinforced or jeopardized by the system's response to the intervention itself (Kotir, 2020).

In adopting the view that policy coherence is an increase in synergies and a reduction in conflicts, it becomes clear that we should approach environmental management as a complex system of moving parts, each impacting one another through emergent behavior. To address such complexity, we must account for a range of dynamic trajectories and feedbacks amidst alternative policy strategies, which may be accomplished through a holistic adoption of *systems-thinking.*

1.1. Systems-thinking archetypes

Systems-thinking involves a series of unique archetypes, often performed in sync with researchers and stakeholders, to understand how complex phenomena operate. These archetypes (i.e., dynamic-thinking, causal-thinking, feedback-thinking, and strategy-thinking) are depicted in Fig. 1 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). Common heuristics used to achieve systems-thinking include:

1) Participatory Models (PM), which derive a collective understanding of the system structure and associated variables through stakeholder participation,
2) Causal Loop Diagrams (CLD), which involve graphical representations of system feedbacks to describe dynamic behavior as reinforcing or balancing, and
3) Fuzzy Cognitive Maps (FCM), which combine aspects of neural networks, system dynamics, and fuzzy logic to assess shifts in state components through "what-if" scenarios.

While such tactics may provide useful insight into complex systems, when used in isolation, they do not capture the full spectrum of systems-thinking (e.g., left-hand side of Fig. 1, adapted from Kim et al., (2017). For example, participatory modeling (PM) has been widely used within environmental science to identify causality, facilitate group learning, and empower communities in policymaking (e.g., Butler and Adamowski, 2015; Inam et al., 2015; Stave, 2002). However, as environmental complexity increases, the number of variables and feedbacks may quickly become overwhelming (Bureš, 2017; Bureš et al., 2020).

Many studies have relied on aggregation of CLD components for manual interpretation (Ryan et al., 2021), which diminishes the causal richness identified in PM sessions (e.g., Brennan et al., 2015). Moreover, large CLDs involve high-order interactions between overlapping feedback loops, which are difficult to decipher using visualization alone (Osoba and Kosko, 2019).

> *"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).

As a result, many CLD-based studies explain system causality using generalized storylines and narratives (e.g., Bahri, 2020; Gebrai et al., 2021), which limit quantitative assessment of system performance (Osoba and Kosko, 2019). System dynamics modeling (SDM) is the translation of causal feedbacks into a numerical model for dynamic simulation (Richmond, 1993). A common SDM technique is a stock-and-flow diagram (SFD), which illustrates system propagation through a set of integral equations. SFDs require rich numerical descriptions of causal dynamics, which are often unavailable for complex human behavior (Bureš et al., 2020). Conversely, FCMs use communal knowledge and perception to parameterize causal relationships from verbal descriptions about how system components respond to each other. FCMs allow for the rapid assessment of system alternatives through "what-if" scenarios according to structural and topological properties of network/graph theory (Voinov et al., 2018). In doing so, FCM-based scenarios facilitate a dynamic understanding of complex human-environmental phenomena that may have otherwise been difficult, or impossible, to assess through traditional empirical approaches (Gray et al., 2014; Özesmi and Özesmi, 2004).

However, the structural characteristics of FCMs pose inherent challenges to basic causal reasoning. Neural networking properties allow FCMs to exhibit forward inferencing (e.g., "what-if" simulations), which reveal *how* the system behaves upon activation. At the same time, cause-effect relations embedded within the model makes backward-chaining (e.g., "why-based" inferencing) extremely difficult (Glykas, 2010). Instead, feedback complexities are entrenched within the numerical simulations and are not easily used to inform *why* the system produces resulting behavior (Harich, 2010). As such, FCM-based scenarios may be deemed black-box methods that obscure the non-linear developments emerging from within the system and how their inter-relationships influence policy relations (Kaljonen et al., 2012).

Stakeholders are interested in understanding why their decisions may influence the system toward a particular trajectory due to the continuous learning nature of adaptive management (McLain and Lee, 1996) and governance partnerships (Elsässer et al., 2022). In real-world applications of participatory modeling, a divide may arise between the stakeholders who are involved in the cognitive mapping and the scientists who present them with complex numerical outputs (Gray et al., 2013). Without a strong basis of causality, stakeholders are unable to form generalizations, and instead, must rely on further computational simulations each time the system changes. To facilitate communication between environmental managers and researchers, we must be able to identify the occurrence of policy coherence within complex systems while also explain its rationale according to embedded causal logic.

1.2. *The need for integrated approaches*

Several state-of-the-art reviews have highlighted a rise in systems-thinking approaches within environmental science (Mashaly and Fernald, 2020; Moon, 2017; Turner et al., 2016; Zomorodian et al., 2018). Systems-based concepts have been used to support decision-making for complex water management systems, such as urban water supply (House-Peters and Chang, 2011), flood protection (Perrone et al., 2020), irrigation (Pluchinotta et al., 2018), and agriculture (Inam et al., 2015). Other studies have emerged where systems-thinking has been applied to nature-based solutions (NBSs) to facilitate an understanding of multiple 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). However, such studies have generally considered the effect of physical processes on system performance (e.g., land use change, climate change, co-benefits production) and have not been widely used to assess policy effectiveness. Moreover, these studies have focused on select components of the systems-thinking paradigm (either dynamics, causality, feedbacks, strategy) and have not fully integrated the strengths of all archetypes (Williams et al., 2017). Studies that have applied systems-thinking to assess policy coherence have often relied on manual interpretation of complex CLD feedback loops and a qualitative presentation of results (e.g., Collins et al., 2013; Paterson and Holden, 2019; Stepp et al., 2009), which may obscure actionable insights. Within the realm of environmental management, FCM-based studies have often highlighted node dominance and scenario-building with lesser discussion of how the feedback loops interacted to produce such behavior (e.g., Giordano et al., 2020; Gómez Martín et al., 2020; Kokkinos et al., 2020; Olazabal et al., 2018; Singh and Chudasama, 2020).

By focusing on either system causality or specific management strategies, we separate the behavior of the system from the structure presumed to cause it (Warren, 2004). As such, there have been calls within the literature to more clearly identify the rationale behind environmental policy effects by exploring the causal loop structure alongside their dynamic, numerical behaviors (de Gooyert et al., 2016). To address this gap, this study integrates qualitative and semi-quantitative approaches across the full spectrum of systems-thinking, thereby revealing systemic interactions that would not be clear from numerical analyses alone, but which also do not require complex data input. The proposed framework promotes a deeper awareness of complexity in the planning of environmental systems and denotes the elucidation of policy coherence as a primary goal of holistic systems-thinking. By amalgamating stakeholder cognition with fuzzy- and causal-logic, this study extends beyond measuring system performance toward understanding its inherent nature amidst complex, policy-driven interactions.

2. Methodological framework

The primary methods used in systems-thinking (PM, CLD, FCM) are well-documented throughout the environmental literature and, as such, are briefly introduced in **Sect. 2.1–2.3**. A means for identifying policy synergy and conflict within FCM-based scenario development is presented in **Sect. 2.4**. In **Sect. 2.5**, an approach is described for weighting CLD-based feedback loops to better understand causality within the FCM-based policy effects. The framework is applied to a case study of environmental management in Houston, TX, USA (**Sect. 3**), and the results of the case study are discussed in **Sect. 4**.

2.1. *Participatory modeling*

Participatory modeling is a stylized approach for defining complex system components and their inter-relationships from stakeholder knowledge (Vennix, 1999). The mental models held by humans describe an internal representation of real systems as shaped by social interactions within the environment, including cognitive biases, values, goals, and experiences (Jones et al., 2011). PM 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 observations shared by a collective group. Common PM techniques include behavioral simulations, role playing games, 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 (1997) for strengthening the scientific basis of PM through documention of best-practices used in community model building. PM scripts encompass a range of topics, including embedded beliefs, system causality, model reflection, and collective action (Hovmand et al., 2011). By elucidating mental models through structured protocols, we are better positioned to evoke the complex human-nature relationships that must be understood for sound decision-making.

2.2. Causal loop diagrams

Causal loop diagrams stem from the PM process to form dynamic hypotheses about how the system functions. In CLDs, 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 links may connect to form balancing loops (odd number of negative links, counteracting change in the system) or reinforcing loops (even number of negative links, propagating change throughout the system). CLDs are conceptual in nature and are intended to increase a holistic understanding of the causality between individual components and sets of components. The resulting model is cyclical, rather than linear, and explains non-linear behavior according to feedback loops. Such loop interactions explain variability in the system response, which is of paramount importance for understanding how the dynamic behavior is governed. The dominant loops within the CLD inform management where key leverage points are located and what types of action would result in the system equalizing or changing exponentially. Policies aimed at such leverage points improve efficiency within the system and help us to better manage emergent behavior (Sternam, 2002).

2.3. Fuzzy cognitive mapping

While CLD's provide information regarding the direction of central relationships of the system, an understanding of how the system will play out over time is necessary for decision-making. For this, fuzzy cognitive maps (FCMs) provide a semi-quantitative basis for simulating complex dynamics according to the system structure and the strengths of variable relationships. FCMs parameterize system relationships according to fuzzy logic by translating qualitative descriptions of strength (e.g., low, medium high) to semi-quantitative weights between − 1.00 (strong negative causality) and + 1.00 (strong positive causality) (Gray et al., 2014). Mathematical pairwise associations between system variables are then summarized within a square adjacency matrix, which may be simulated to better understand current and projected system states (Özesmi and Özesmi, 2004). The dynamics of FCM models are specified by state vectors, in which the state vector of one variable depends on the state vectors of all other connected variables over time.

To simulate the FCM network, variables are denoted as equivalent to neurons that can be activated at the onset of the simulation while also adopting in-between states. An activation value of + 1.00 indicates the variable is strengthened to the maximum possible weight (known as "clamping"), thereby influencing all connected variables throughout the simulation. Conversely, an activation value of 0 means the variable does not change at the on-set of simulation and is only influenced by the dynamics of causal connections. The activated variable state is multiplied by the adjacency matrix at each time step, which propagates throughout the simulation according to causality, thereby spreading in a non-linear fashion until the system reaches equilibrium (Jetter and Schweinfort, 2011). When applied to policymaking, a series of artificial scenarios are simulated by "clamping" select management variables and comparing end-state vectors against a baseline scenario. The extent of change between the activated and the baseline scenario projects how the system will respond to unique policies according to dynamic interactions within the model.

2.4. Identifying synergies & conflicts

Policy analysis describes the sensitivity of the model to human interaction. By altering one (or more) of the system variables and assessing the resulting outcomes, patterns begin to emerge that reveal which policies would lead to optimal (or sub-optimal) results (Barlas, 2002). Here, FCM-based scenario modeling is used to simulate various management strategies associated with NBSs and assess changes to the state of NBS implementation. Specifically, end-state vectors for various multi-policy strategies are compared to identify areas of synergy or conflict, as described by Eqs. 1-2.

Policy synergy occurs when a strategy produces better output than the sum of any individual components comprising the given cohort, defined by

$$\Delta S_{k(j=n)} > \sum_{j\in A}\Delta S_{kj}, \quad A = \left\{\mathbb{N} : \sum A = n\right\} \tag{1}$$

where ΔS_k describes the percent change of the end-state vector for the system goal variable within management strategy (k), j is the number of unique policies being combined within strategy k to a maximum of n total policies. [Note: j is within the set of natural integers (A) that sum to n (e.g., if $n = 6$, $j = \{1,5\}|\{2,4\}|\{3,3\}|\{2,2,2\}|\{1,2,4\}$, etc.)].

Policy conflict occurs when adding any extra components to the strategy results in less output than had the components not been combined, such that

$$\Delta S_{k(j=n)} < \bigvee\sum_{j\in B}\Delta S_{kj}, \quad B = \{\mathbb{N} : \sum B < n\} \tag{2}$$

where j is within the set of natural integers (B) that sum to be less than n. The logical *or* operator ($\vee$) means that any combination of ΔS_{kj} which is greater than ΔS_{kn} would result in policy conflict (e.g., if $n = 4$, conflict occurs for any $\Delta S_{kj} > \Delta S_{k4}$, where $j = \{1\}|\{2\}|\{3\}|\{1,1\}|\{1,2\}|\{2,1\}$, etc.).

2.5. Explaining policy coherence

Areas of synergy and conflict are then compared to reinforcing and balancing feedbacks to better understand the policy implications of embedded causal logic.

Here, the weighted strengths of causal feedback loops are defined by

$$w_f^{(t=0)} = \pm\frac{\sum_{i=1}^{M}\sum_{j=1}^{M}|w_{ij}|}{M} \tag{3}$$

where w_f describes the average weighted strength of each feedback loop f at simulation time $t = 0$, w_{ij} is the fuzzy strength between variable i and j, and M is the total number of unique connections within the feedback loop. The loop strength is assigned a polarity of '+ ' for reinforcing and '-' for balancing.

3. Case study: nature-based solutions

To demonstrate the methodology described in **Sect. 2**, a case study was conducted in Houston, TX, USA regarding policies for improved adoption of nature-based solutions (NBSs). As climate change and urban densification continue to rise, traditional stormwater systems are being challenged by limited conveyance capacitance and expensive mitigation strategies (ASCE, 2020). Many flood-prone communities, such as Houston, are considering soft-scale solutions to complement drainage networks by emulating natural watershed processes and limiting the amount of stormwater runoff entering the system (Demuzere et al., 2014). In addition to mitigating stormwater, NBSs have been associated with numerous co-benefits, including improved mental and physical

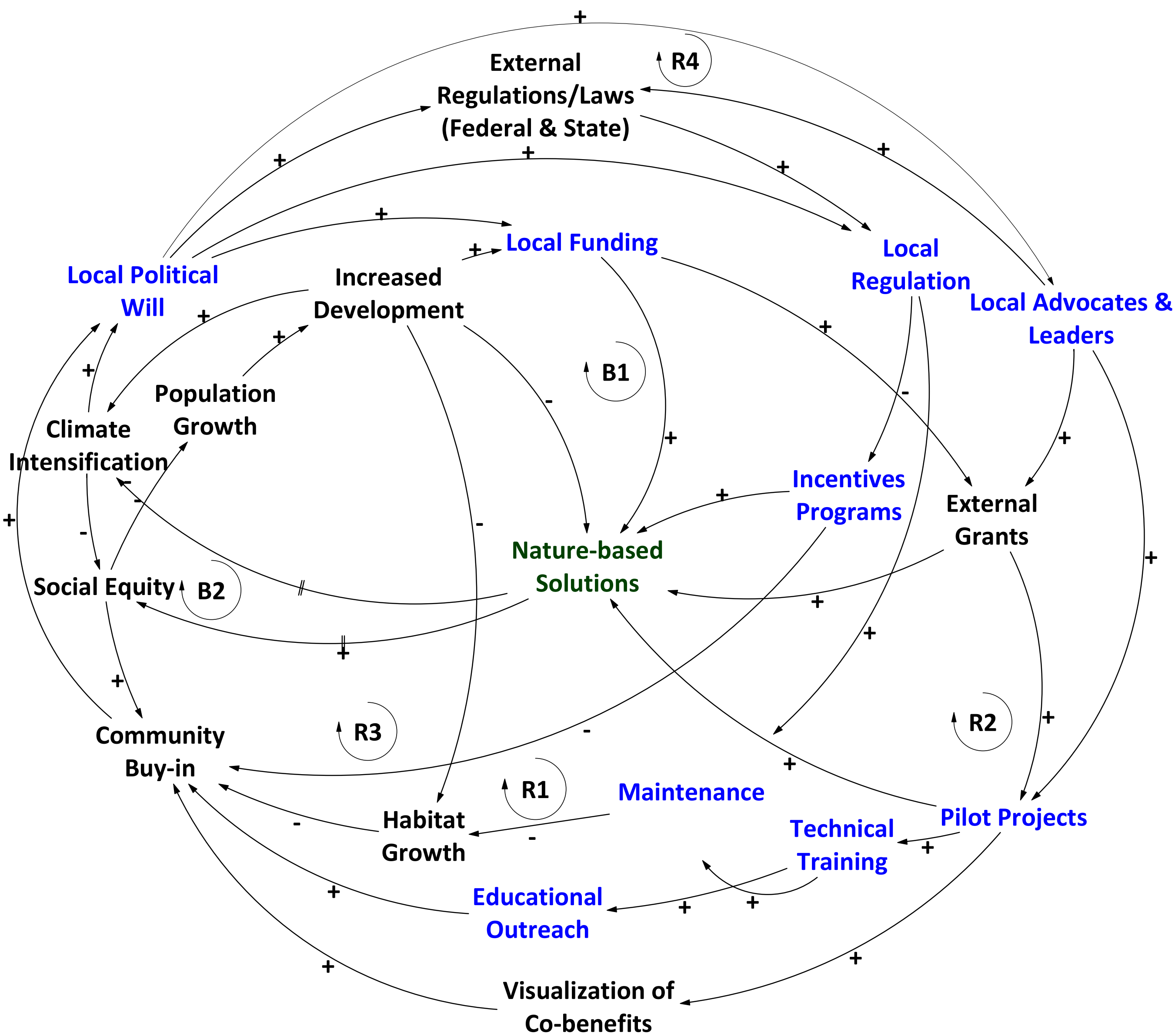

Fig. 2. Stakeholder-derived causal loop diagram depicting social-institutional factors involved with implementation of nature-based solutions. Blue = management opportunities, within the scope of stakeholder influence. Black = exogenous variables, outside the scope of stakeholder influence. Green = system goal variable. Polarity of feedback loops is indicated by '+ ' for positive (same-direction causation) and '-' for negative (opposite-direction causation). Reinforcing and balancing feedback loops are denoted by direction and nomenclature 'R' and 'B', respectively. Note: Color should be maintained when printed.

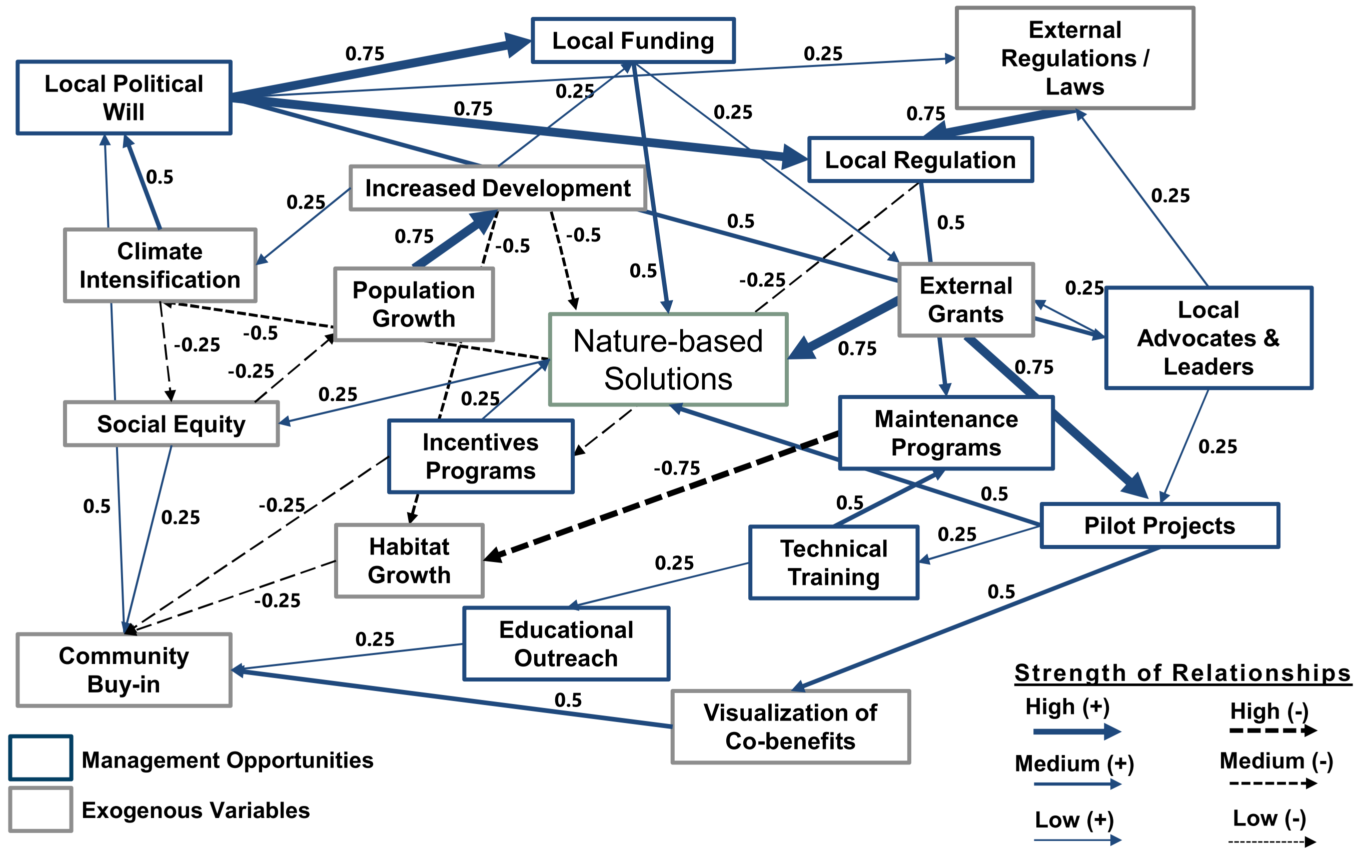

Fig. 3. Fuzzy cognitive map, as elicited by the stakeholder group for describing NBS socio-institutional challenges as either management opportunities (within the scope of stakeholder influence) or exogenous variables (outside the scope of stakeholder influence). Blue arrows = '+ ' polarity. Black, dashed arrows = '-' polarity. Strengths of connecting arrows are represented by line weights, as defined in the legend (low strength = +/- 0.25, medium strength = +/- 0.50, high strength = +/- 0.75). Note: Color should be maintained when printed.

health, social vulnerability, economic prosperity, air and water quality, temperature regulation, and ecosystem conservation. Although such benefits have been broadly observed throughout the literature (see Table S.1), widespread adoption of NBS has remained stunted due to socio-institutional complexities associated with environmental policy-making.

For example, observational case studies have identified several key challenges to NBS uptake, including community perceptions and understanding of NBS functionality (Baptiste et al., 2015), cultural values pertaining to risk and/or change,(Derkzen et al., 2017), and institutional frameworks associated with funding, regulations, leadership, technical design, and maintenance (Solheim et al., 2021; Zuniga-Teran et al., 2020) (summarized in Table A.1). While these barriers have been studied as isolated events, we lack a general understanding of how such factors operate holistically to influence one another. A recent workshop conducted by the UNEP's Intergovernmental Panel on Climate Change (IPCC) emphasized that complexities within multi-functional policy-making and their physical-social feedbacks are key impediments to NBS uptake. The IPCC recommended a shift toward co-produced knowledge between practitioners and researchers to overcome such implementation challenges (Frantzeskaki et al., 2019). An example of co-produced knowledge and systems-thinking within the realm of NBS is demonstrated by the following case study.

3.1. Eliciting stakeholder knowledge

A virtual workshop was held to capture the mental models of experts who had been involved with NBS implementation efforts in Houston, TX, USA (Text S.1, Table S.2). The PM workshop was facilitated by guiding the stakeholder group through a series of interactive scripts for understanding system causality, defining key relationships, identifying feedback strengths, and reflecting on model-based insights (Text S.2). During the PM process, stakeholders were asked to consider how unique factors have limited or advanced NBS efforts according to their lived experiences. Throughout the semi-structured process, participants identified numerous causal factors associated with NBS implementation, which were documented in real-time and grouped according to key socio-institutional themes (e.g., challenges and barriers, management opportunities, and exogenous factors) (Fig. S.1, Table S.3).

The facilitator selected several variables from the elicitation exercise and drew them as nodes within a web-based whiteboard. Sample causal relationships and feedback loops were described and demonstrated visually within the shared interface. The participants were asked to describe their understanding of causal feedbacks between the different elements, which fostered robust discussions of the underlying system dynamics. Individual stakeholders discussed their interpretation of causal relationships, which led to group agreement or uncertainty, often stimulating deeper discussions of system causality. As the stakeholders communicated, the workshop facilitator moved variable nodes on the screen and marked the causal links to correspond with the group consensus. During the live modeling session, CLD connections were drawn as one-way arrows between variables using traditional polarity notations (e.g., 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 were also asked to define, qualitatively, the perceived strength of each causal feedback. Feedbacks that were deemed to be particularly strong were denoted with three causal arrows, and moderate connections were identified with two overlapping arrows. All other causal relationships were depicted with a single arrow (Fig. S.2). This approach was meant to

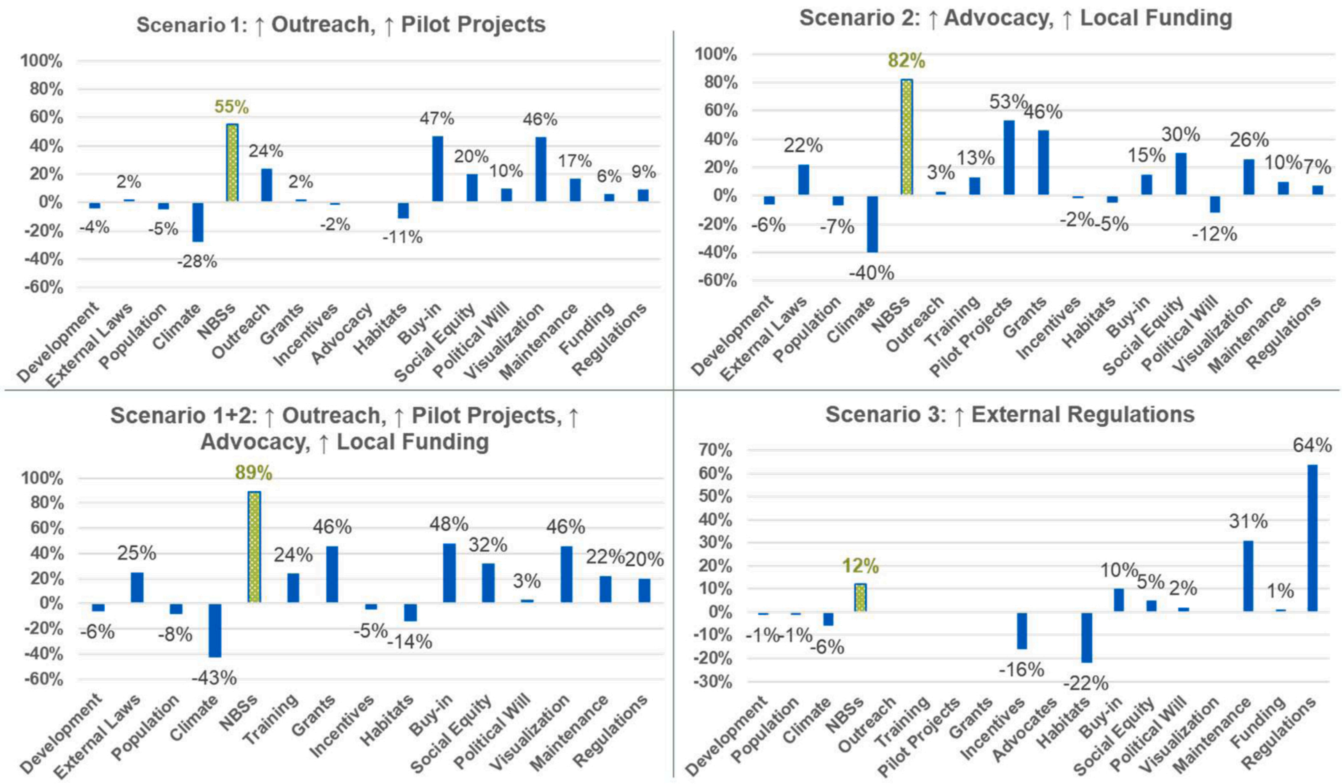

Fig. 4. Scenario output from *Mental Modeler* (FCM-based simulation software), where the policy variable(s) listed in each chart title were activated through clamping to a value of + 1.00, and changes in each variable state vector between the status quo and the final dynamic simulation were graphed as a relative percentage (ΔS_{NBS}). The shifts in state vector magnitude for nature-based solutions, which were the goal variable for this system, are shown in green.

mimic the use of color-coded sticky notes used in live PM workshops (Andersen and Richardson, 1997; Inam et al., 2015), thereby facilitating a virtual environment with interactive group discussions and real-time causal loop diagramming.

After the workshop, the causal loop sketch was translated into a composite CLD using *Vensim* software (Fig. 2). Several NBS policy leaders who were not involved in the stakeholder workshop reviewed the composite CLD for overall agreement and coherency. When areas of ambiguity were noted, the modeler synthesized causal connections and system variables to capture key components (e.g., floods and climate change were noted as providing a similar exogenous impact within the system, which were thus synthesized as one variable). A verbal transcript of the recorded session was reviewed during the translation process to ensure the variables and causal relationships were correctly represented. The optimized CLD was emailed to all workshop participants for validation, and no discrepancies were noted.

3.2. Defining fuzzy weights

The preceding steps identified the stakeholders' understanding of system variables and how they interact amongst one another to facilitate, or hinder, local NBS implementation. These system components provided the qualitative foundation for defining the system structure. Next, the CLD was transposed into a semi-quantitative FCM model using the web-based mapping suite *Mental Modeler* (Gray et al., 2013, 2015). The degree of influence for each causal link was defined with fuzzy logic according to stakeholder perceptions from the PM session. Fuzzy weights were used to identify the strengths of system feedbacks

Table 1
Summary of feedback loops identified within the stakeholder-led causal loop diagram. R = reinforcing feedback loop (even number of negative connections). B = balancing feedback loop (odd number of negative connections). The direction of polarity and strength of each feedback is shown.

Loop	Variable Connections	$w_f^{(t=0)}$
R1	Local Political Will $\underset{\rightarrow}{+0.75}$ Local Regulation $\underset{\rightarrow}{+0.50}$ Maintenance $\underset{\rightarrow}{-0.75}$ Habitat Growth $\underset{\rightarrow}{-0.25}$ Community Buy-in $\underset{\rightarrow}{+0.50}$ Local Political Will	0.35
R2	Local Political Will $\underset{\rightarrow}{+0.75}$ Local Funding $\underset{\rightarrow}{+0.25}$ External Grants $\underset{\rightarrow}{+0.75}$Pilot Projects $\underset{\rightarrow}{+0.50}$ Visualization of Co-benefits $\underset{\rightarrow}{+0.50}$ Community Buy-in $\underset{\rightarrow}{+0.50}$Local Political Will	0.54
R3	Local Political Will $\underset{\rightarrow}{+0.25}$ External Regulations / Laws $\underset{\rightarrow}{+0.75}$ Local Regulation$\underset{\rightarrow}{-0.25}$ Incentives Programs $\underset{\rightarrow}{-0.25}$ Community Buy-in $\underset{\rightarrow}{+0.50}$Local Political Will	0.40
R4	Local Political Will $\underset{\rightarrow}{+0.50}$ Local Advocates $\underset{\rightarrow}{+0.25}$ Pilot Projects $\underset{\rightarrow}{+0.25}$ Technical Training $\underset{\rightarrow}{+0.25}$ Educational Outreach $\underset{\rightarrow}{+0.25}$Community Buy-in $\underset{\rightarrow}{+0.50}$Local Political Will	0.33
B1	Local Political Will $\underset{\rightarrow}{+0.75}$ Local Funding $\underset{\rightarrow}{+0.50}$ Nature-based Solutions $\underset{\rightarrow}{-0.50}$ Climate Intensification $\underset{\rightarrow}{+0.50}$ Local Political Will	- 0.56
B2	Social Equity $\underset{\rightarrow}{-0.25}$ Population Growth $\underset{\rightarrow}{+0.75}$ Increased Development $\underset{\rightarrow}{+0.25}$ Local Funding $\underset{\rightarrow}{+0.25}$Nature-based Solutions $\underset{\rightarrow}{+0.50}$ Social Equity	- 0.40

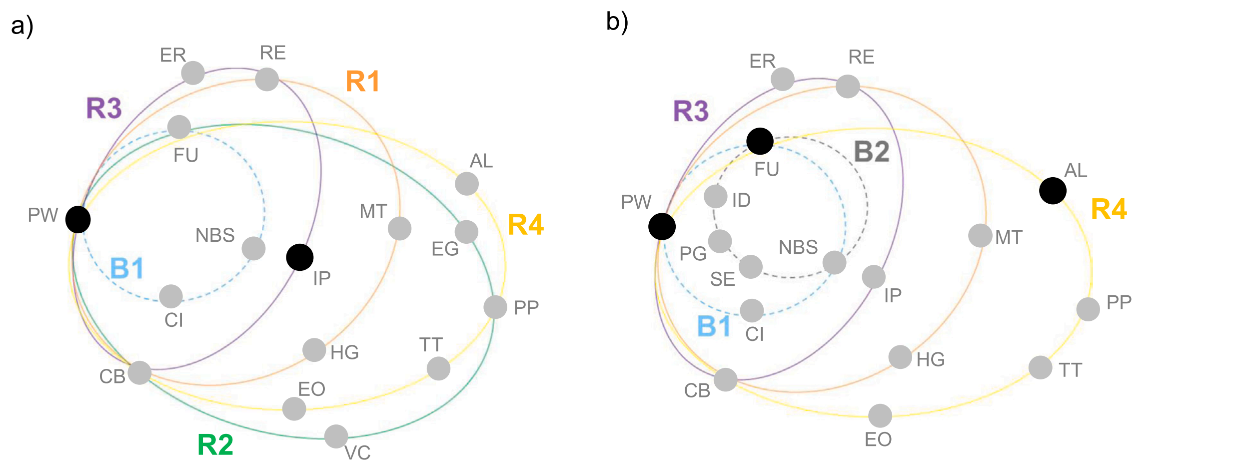

Fig. 5. Illustration of causal feedback loop interactions associated with activation of select policy variables (black), and all associated causal variables (grey) for **a)** policy synergy and **b)** policy conflict. [Educational Outreach = EO, Technical Training = TT, Pilot Projects = PP, Incentives Programs = IP, Advocacy and Leadership = AL, Political Will = PW, Maintenance = MT, Local Funding = FU, Local Regulations = RE, External Regulations = ER, Community Buy-in = CB, Habitat Growth = HG, Visualization of Co-benefits = VC, External Grants = EG, Nature-Based Solutions = NBS, Climate Intensification = CI, Social Equity = SE, Population Growth = PG, Increased Development = LD].

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 (Fig. 3). A score of + 1.00 was reserved for "clamping" key decision variables for scenario development (e.g., Gray et al., 2015) as described in **Sect. 2.3**. The system structure was summarized by a square adjacency matrix (*i* x *j* variables), demonstrated in Table S.3.

3.3. Simulating management strategies

The weighted FCM was used to simulate various "what-if" management strategies (where a strategy comprises one or more individual policies) to better understand how a change in local policy would impact the relative state change of the NBS goal variable. Out of the 19 total system variables, the final FCM contained 9 management opportunities which were deemed to be within the stakeholders' sphere of influence (i.e., 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)). From these variables, 129 fuzzy scenarios were identified by assuming the stakeholders would implement either a single policy strategy (n = 9), a strategy combining two policies (n = 36), or a strategy combining three policies (n = 84),

The simulations in *Mental Modeler* use the adjacency matrix (Table S.4) to represent the strengths of interconnections and state vectors to characterize the degree of variable change once a scenario is activated. As such, the modeling suite quantifies 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. The specific mathematical functions used within *Mental Modeler* include the Kosko's activation rule and the hyperbolic transformation function, which are further detailed by Gray et al., (2015, 2013). After the system stabilizes (typically before 10 iterations), the end-state vector changes are output as a relative percentage. Fig. 4 demonstrates how activating a unique set of policy nodes may impact a variety of state shifts in the remaining variables, both positive and negative, according to the model structure and the system dynamics.

Areas of policy synergy and conflict were then calculated from the simulation outputs (per Eqs. 1–2) to identify which combinations of management strategy produced cohesive or resistant outcomes. The strengths of the reinforcing and balancing feedback loops were also calculated (per Eq. 3) to better understand the observed policy effects in accordance with the system's causal structure.

4. Results

4.1. Characterizing system causality

The stakeholder workshop revealed 19 unique variables and 37 causal links associated with NBS implementation and management strategy in Houston, TX. These results corresponded well with the average number of variables (n = 23) and connections (n = 37) observed in socio-environmental systems, according to a meta-study by Özesmi and Özesmi (2004). According to *Vensim*, the CLD variables connected to form 97 unique feedback loops. A key sampling of four reinforcing loops and two balancing loops were chosen to demonstrate the systems-thinking framework (Fig. A.1). During the PM session, the stakeholders were asked to define the fuzzy strengths of causal connectivity between system variables, which were used to determine the average weighting of each feedback loop at the onset of FCM-based simulation (Eq. 3). Table 1 summarizes the polarity and weighted strength for each feedback loop. Here, reinforcing loop R1 was noted as the "Maintenance Loop", whereby improved maintenance from local regulations would reduce habitat over-growth and improve community buy-in of NBS technologies, driving political will and 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, thereby enhancing visualization of co-benefits, and strengthening 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 voluntary incentives programs. This, in turn, would drive local political will and trigger additional influence of federal and state regulations. Reinforcing loop R4, the "Advocacy Loop", describes the condition where political will could be used to increase the amount and influence of NBS advocacy groups and local champions, thereby driving implementation of additional pilot projects, trainings, and outreach to bolster community acceptance.

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 subsequent impervious development

Table 2
Fuzzy cognitive mapping-based scenario output used to understand policy effectiveness on the final state change ΔS_k of nature-based solutions. k = nomenclature of each strategy. [Educational Outreach = EO, Technical Training = TT, Pilot Projects = PP, Incentives Programs = IP, Advocacy and Leadership = AL, Political Will = PW, Maintenance = MT, Local Funding = FU, Local Regulations = RE].

1 Policy (n = 1)		2 Policies (n = 2)		3 Policies (n = 3)							
k	ΔS_{k1}	k	ΔS_{k2}	k	ΔS_{k3}	k	ΔS_{k3}	k	ΔS_{k3}	k	ΔS_{k3}
EO	9%	TT-MT	7%	EO-TT-PP	53%	EO-PW-RE	55%	TT-FU-RE	63%	IP-MT-RE	18%
TT	5%	TT-FU	66%	EO-TT-IP	24%	EO-MT-FU	67%	PP-IP-AL	71%	IP-FU-RE	77%
PP	48%	TT-RE	3%	EO-TT-AL	42%	EO-MT-RE	10%	PP-IP-PW	86%	AL-PW-MT	68%
IP	12%	PP-IP	60%	EO-TT-PW	56%	EO-FU-RE	63%	PP-IP-MT	62%	AL-PW-FU	80%
AL	36%	PP-AL	60%	EO-TT-MT	14%	TT-PP-IP	62%	PP-IP-FU	90%	AL-PW-RE	67%
PW	56%	PP-PW	76%	EO-TT-FU	67%	TT-PP-AL	61%	PP-IP-RE	62%	AL-MT-FU	81%
MT	5%	PP-MT	51%	EO-TT-RE	9%	TT-PP-PW	76%	PP-AL-PW	79%	AL-MT-RE	36%
FU	65%	PP-FU	84%	EO-PP-IP	64%	TT-PP-MT	51%	PP-AL-MT	61%	AL-FU-RE	79%
RE	0%	PP-RE	47%	EO-PP-AL	63%	TT-PP-FU	84%	PP-AL-FU	88%	PW-MT-FU	73%
		IP-AL	50%	EO-PP-PW	76%	TT-PP-RE	48%	PP-AL-RE	58%	PW-MT-RE	55%
2 Policies (n = 2)		IP-PW	74%	EO-PP-MT	54%	TT-IP-AL	53%	PP-PW-MT	76%	PW-FU-RE	72%
k	ΔS_{k2}	IP-MT	18%	EO-PP-FU	84%	TT-IP-PW	64%	PP-PW-FU	85%	MT-FU-RE	63%
EO-TT	11%	IP-FU	76%	EO-PP-RE	50%	TT-IP-MT	20%	PP-PW-RE	75%		
EO-PP	52%	IP-RE	16%	EO-IP-AL	55%	TT-IP-FU	77%	PP-MT-FU	84%		
EO-IP	21%	AL-PW	68%	EO-IP-PW	74%	TT-IP-RE	19%	PP-MT-RE	48%		
EO-AL	41%	AL-MT	39%	EO-IP-MT	27%	TT-AL-PW	68%	PP-FU-RE	82%	**Synergy:**	
EO-PW	56%	AL-FU	81%	EO-IP-FU	77%	TT-AL-MT	40%	IP-AL-PW	81%	**Conflict:**	
EO-MT	13%	AL-RE	35%	EO-IP-RE	24%	TT-AL-FU	81%	IP-AL-MT	53%		
EO-FU	66%	PW-MT	56%	EO-AL-PW	68%	TT-AL-RE	37%	IP-AL-FU	88%		
EO-RE	8%	PW-FU	73%	EO-AL-MT	43%	TT-PW-MT	56%	IP-AL-RE	52%		
TT-PP	50%	PW-RE	55%	EO-AL-FU	81%	TT-PW-FU	73%	IP-PW-MT	74%		
TT-IP	18%	MT-FU	66%	EO-AL-RE	39%	TT-PW-RE	55%	IP-PW-FU	84%		
TT-AL	39%	MT-RE	2%	EO-PW-MT	56%	TT-MT-FU	66%	IP-PW-RE	74%		
TT-PW	56%	FU-RE	62%	EO-PW-FU	73%	TT-MT-RE	4%	IP-MT-FU	77%		

while also strengthening community buy-in. Loop R2 exhibited the strongest potential for system amplification, while loop B1 displayed the strongest equalizing capacitance within the system. Loops R1 and R4 demonstrated relatively weak functions of system propagation, while loop R3 and B2 provided moderate reinforcing and balancing effects, respectively.

4.2. FCM-based policy effectiveness

The dynamics of the system resulted in a positive increase in the state of the NBS variable for all of the modeled management strategies, except for local regulations, which resulted in no impact. The relative change in NBS implementation for each management strategy is summarized in Table 2. Here, ΔS_k represents the change in state vector for the NBS variable after unique policy strategies were activated. 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 green. For example, the combined strategy IP-PW (incentives programs and political will) resulted in an NBS state change of $\Delta S_{IP\text{-}PW}$= 74%. Had each of these policies been implemented separately, and the dynamic interactions not considered, the NBS state-vector would have only increased by $\Delta S_{IP\text{-}PW}$= 68% (e.g., ΔS_{IP}=12%+ΔS_{PW}=56%). Management strategies that were conflicting, meaning they interacted to produce an NBS state vector that was less than that of the corresponding individual policies, are noted in orange. For example, while strategy AL-PW-FU (advocacy and leadership, political will, local funding) resulted in a large state-vector shift ($\Delta S_{AL\text{-}PW\text{-}FU}$=80%), the policy components worked against one another to produce less output than had they been implemented separately. Specifically, the shift in NBS state-vector for strategy AL-FU was $\Delta S_{AL\text{-}FU}$= 81%. In other words, the addition of PW decreased the relative policy effectiveness by 1%.

This approach is useful for cycling through numerous policy options and their combinations to guide decision-making, particularly when such decisions are cyclical in nature (i.e., where each decision alters the system environment and impacts the state values of all connected variables). However, sole reliance upon FCM-based modeling does not explain why unique strategies interacted to trigger synergies or conflicts. For this, we must explore the causal feedback loops embedded within the system structure and how activation of key policy variables might trigger various levels of reinforcing or balancing behavior.

4.3. Making sense of policy coherence

Here, the management strategies discussed in **Sect. 4.2** are further explored to assess the influence of feedback loops on policy coherence. In considering the synergy between IP and PW, we may locate each policy variable within the composite CLD and examine their associated feedback loops. As demonstrated in Fig. 5**a**, political will (PW) is located at the confluence of five feedback loops, each with unique strengths and polarities (R1, R2, R3, R4, B1). Incentives programs (IP) are only located

Table 3
Rank of management strategies (k) and their corresponding NBS end-state vector values (ΔS_k), describing the efficacy of policy combinations toward furthering implementation of nature-based solutions in the case study model. [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.].

No.	Upper Quartile (Q3)		Middle Quartile (Q2)				Lower Quartile (Q1)	
	Strategy (k)	Efficacy (ΔS_k), %	Strategy (k)	Efficacy (ΔS_k), %	Strategy (k)	Efficacy (ΔS_k), %	Strategy (k)	Efficacy (ΔS_k), %
1	PP-IP-FU	90%	EO-IP-PW	74%	TT-PP-AL	61%	EO-AL-MT	43%
2	PP-AL-FU	88%	IP-PW-MT	74%	PP-AL-MT	61%	EO-TT-AL	42%
3	IP-AL-FU	88%	IP-PW-RE	74%	PP-IP	60%	EO-AL	41%
4	PP-IP-PW	86%	PW-FU	73%	PP-AL	60%	TT-AL-MT	40%
5	PP-PW-FU	85%	EO-PW-FU	73%	PP-AL-RE	58%	TT-AL	39%
6	PP-FU	84%	TT-PW-FU	73%	EO-PW	56%	AL-MT	39%
7	EO-PP-FU	84%	PW-MT-FU	73%	TT-PW	56%	EO-AL-RE	39%
8	TT-PP-FU	84%	PW-FU-RE	72%	PW-MT	56%	TT-AL-RE	37%
9	PP-MT-FU	84%	PP-IP-AL	71%	EO-TT-PW	56%	AL-MT-RE	36%
10	IP-PW-FU	84%	AL-PW	68%	EO-PW-MT	56%	AL-RE	35%
11	PP-FU-RE	82%	EO-AL-PW	68%	TT-PW-MT	56%	EO-IP-MT	27%
12	AL-FU	81%	TT-AL-PW	68%	PW-RE	55%	EO-TT-IP	24%
13	EO-AL-FU	81%	AL-PW-MT	68%	EO-IP-AL	55%	EO-IP-RE	24%
14	TT-AL-FU	81%	EO-TT-FU	67%	EO-PW-RE	55%	EO-IP	21%
15	IP-AL-PW	81%	EO-MT-FU	67%	PW-MT-RE	55%	TT-IP-MT	20%
16	AL-MT-FU	81%	AL-PW-RE	67%	TT-PW-RE	55%	TT-IP-RE	19%
17	AL-PW-FU	80%	EO-FU	66%	EO-PP-MT	54%	TT-IP	18%
18	PP-AL-PW	79%	TT-FU	66%	EO-TT-PP	53%	IP-MT	18%
19	AL-FU-RE	79%	MT-FU	66%	TT-IP-AL	53%	IP-MT-RE	18%
20	EO-IP-FU	77%	TT-MT-FU	66%	IP-AL-MT	53%	IP-RE	16%
21	TT-IP-FU	77%	EO-PP-IP	64%	EO-PP	52%	EO-TT-MT	14%
22	IP-MT-FU	77%	TT-IP-PW	64%	IP-AL-RE	52%	EO-MT	13%
23	IP-FU-RE	77%	EO-PP-AL	63%	PP-MT	51%	EO-TT	11%
24	PP-PW	76%	EO-FU-RE	63%	TT-PP-MT	51%	EO-MT-RE	10%
25	IP-FU	76%	TT-FU-RE	63%	TT-PP	50%	EO-TT-RE	9%
26	EO-PP-PW	76%	MT-FU-RE	63%	IP-AL	50%	EO-RE	8%
27	TT-PP-PW	76%	FU-RE	62%	EO-PP-RE	50%	TT-MT	7%
28	PP-PW-MT	76%	TT-PP-IP	62%	TT-PP-RE	48%	TT-MT-RE	4%
29	PP-PW-RE	75%	PP-IP-MT	62%	PP-MT-RE	48%	TT-RE	3%
30	IP-PW	74%	PP-IP-RE	62%	PP-RE	47%	MT-RE	2%

on loop R3. Since R3 is connected to the same feedback loops as PW, via the PW node, activation of both policies generates a very strong response from all four reinforcing loops in the diagram. Even though balancing loop B1 is trigged in this scenario, the combination of reinforcing effects is much stronger than the equalizing effects of B1 (e.g., $\sum_{i=1}^{4} w_{Ri} \gg w_{B1}$). In other words, local activism produces a synergistic effect that propagates a strong, positive trajectory throughout the system through improved maintenance, funding, community buy-in, and leadership. Once activated, these loops are not easily dampened by the balancing effects of the climate loop.

In considering the conflicting nature of AL-PW-FU, we may observe the feedback loops demonstrated in Fig. 5**b**. Activation of PW exhibits the same effects as described previously. Activation of AL triggers loop R4, which when combined with PW, results in a strong reinforcing effect. However, when node FU is activated, both balancing loops B1 and B2 are triggered, thereby dampening the system trajectory. According to the stakeholders, FU was presumed to have a positive causal association with local development and population growth, which negatively impact urban greening. Since loop R4 is relatively weak, activation of AL does not offset these balancing effects. While this strategy does not shift the system into a negative state (i.e., policy resistance), it could be argued that additional FU alongside AL-PW is not an efficient use of resources.

Additional insights may be derived by ranking the NBS end-state vectors for all strategies and noting the occurrence of specific policies (Table 3). Variables PP, PW, and FU are noted within many high-efficiency strategies (i.e., upper quartile). Both PP and PW are located at the confluence of several strong reinforcing loops, which explains why they are highly associated with greater NBS impact in the system. FU is a component of both the strong balancing loops B1-B2 and the strong reinforcing loop R2, which may have trended the system toward equilibrium had there been no other dynamic forces involved. However, loop R2 triggers several other reinforcing loops, thereby potentially amplifying systematic change, depending on the activity of other associated variables. Other system variables that interacted with loop B1, but which did not have strong reinforcements to counteract the balancing forces, showcased less favorable outcomes. Conversely, variables TT, MT, and EO tended to exhibit weak efficiencies when combined with other policy options. An assessment of the associated causal structures demonstrated 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. While such manual interpretations of all policy combinations and feedback loops within the system would quickly become burdensome, the approach presented here provides a rapid visual assessment of how strategies may interact within the system dynamics to produce synergies or conflicts according to the embedded causal logic. When combined with the quantitative strengths of scenario-building, we are able to gain a fuller picture of policy effects associated with stakeholder-defined, complex human-nature systems.

5. Methodological limitations

Several limitations to the methodology described here stem from the choice in FCM software (e.g., *Mental Modeler*), which restricts user modification. *Mental Modeler* was designed to be used by, or alongside, stakeholders as a quick and simple tool for FCM mapping and simulation. As such, the software suite contains no computer learning-based algorithms, and system activation is only possible through Kosko's inference rule (Gray et al., 2015). In essence, *Mental Modeler* lacks extensive capabilities for re-configuring the internal mechanisms of the model, such as transfer functions, number of iterations, or learning-based inference tools. Several papers have described these limitations of *Mental Modeler* (e.g., Felix et al., 2019; Nikas et al., 2019) while also highlighting how it is an optimal choice for low-entry and user-friendly FCM-based stakeholder modeling. A deeper investigation of FCM-based modeling, activation rules, and inference capabilities is noted by Nápoles et al. (2018) and Papageorgiou et al. (2018). Using simplified FCM to better understand how the system shifts in terms of end-state vector values has been shown within the socio-ecological literature to be a valid use of *Mental Modeler* (Özesmi and Özesmi, 2004). As such, the emphasis of this article is to describe a learning-based framework for spurring systems-thinking and collaboration across diverse stakeholders while extracting both the *why* and the *how* of general policy effect. Such a framework, naturally, is not intended for high-resolution predictive capabilities of system dynamics models.

Moreover, it should be noted that Eq. 3 describes the feedback loop strength at the onset of FCM-based simulation. Naturally, the weighted strengths will change during the dynamic simulation as the loops are influenced by other system components over time. With 97 causal feedback loops within the case study, manual interpretation is impractical. However, by identifying the initial strengths of key feedback loops and comparing them to policy synergies and conflicts, it becomes possible to complement our understanding of general system behavior with insights regarding loop structure. Finally, this simplified approach to calculating policy synergy or conflict does not consider dynamic time effects of separate implementation strategies. For example, strategy EO-PW-RE is considered a conflict according to Eq. 2 (e.g., $55\%(\Delta S_{EO-PW-RE})\langle 56\%(\Delta S_{EO-PW}))$. By adding RE, the system exhibited less output than had just EO-PW been implemented. However, the shift in end-state-vector for EO-PW-RE depends on the order of implementation. This study assumed that single-policy strategies were implemented after multi-policy strategies. Had RE been implemented first, various system states would have shifted in accordance with RE-based causality. A subsequent simulation for EO-PW should consider the propagation effects of the previous policy implementation(s). Such dynamics were outside the scope of this study, and future research could explore the sensitivity of adjoining impacts associated with the timing of unique policy combinations.

6. Insights & discussion

This case study highlights how holistic systems-thinking may be used to investigate complex policy effects while also fostering adaptive learning opportunities. During the PM workshop, unique belief schemas were noted regarding the group's initial perception of system performance. Some of these assumptions conflicted with general findings in the NBS literature (e.g., Table S.1) while others were contradicted by the FCM-based simulation results (e.g., Table 3). For example, the stakeholders felt that a lack of external laws regarding sustainable development was the main hindrance to local NBS implementation. The stakeholders presumed that if the external regulations (ER) could be strengthened, the remaining components of the system would somehow transform to work seamlessly together for optimal impact. However, the NBS literature suggests that collaboration across socio-institutional scales is paramount for successful policymaking. Fig. 4 demonstrated how a streamlined focus on ER results in significantly fewer NBSs when compared with collaborative management opportunities.

The stakeholders were also wary of the role played by enhanced visualization of co-benefits from NBS production. The group insisted that locals were more concerned with stormwater mitigation capacitance due to the flood-prone nature of Houston. They conceded that while a causal connection exists, the environmental and social co-benefits associated with NBSs were significantly less valued in the local culture and would not enhance the overall system performance. While the stakeholders believed that visualization of NBS co-benefits did not serve a primary role in local uptake, Tables 2–3 demonstrated how improved pilot projects (PP) would trigger positive reinforcing outcomes of co-benefit visualization, strongly impacting positive NBS development.

Such findings emphasize how the beliefs of system behavior at the forefront of cognition may conflict with the actual system dynamics defined by deeply embedded causal knowledge. As a result, stakeholders may leave PM sessions with self-confirming inferences that do not represent the system they had collectively defined. The framework presented here allows us to work alongside decision-makers in exploring unique policy effects using mathematical models and causal reasoning. When we identify an outcome which contradicts group perception, we are able to foster self-reflection and adaptive learning. For instance, after the conclusion of this study, the FCM model was simulated alongside key resilience leaders in Houston, TX. These leaders observed a positive response throughout the system when social equity was strengthened. Over the course of several meetings, initial perceptions regarding system causality and dominance began to shift in accordance with the outputs described in **Sect. 4**. Indeed, this interactive process facilitated a shift in local NBS decision-making. Following the group-learning exercises, local leaders requested assistance with transitioning from hydrology-based NBS planning to a composite framework involving hydrologic, environmental, and social co-benefits (e.g., equity-based planning) (Castro, 2022).

Initial stakeholder perceptions do not always match our empirical findings of system causality and dominance. By using causal reasoning and fuzzy logic to identify and counteract limitations in stakeholder beliefs, this study transposed dominant system properties into actionable insights for ongoing adaptive management. Specifically, by combining complex belief systems across institutional scales and by using a mixed-methods approach to systems-thinking, we may better match the system dynamics to group cognition within a cyclic process of discovery and actualization.

7. Conclusion

Nearly three decades ago, at the dawn of climate awareness and environmental politicization, systems scientist Barry Richmond urged us to embrace holistic systems-thinking as key for overcoming policy resistance.

> *"The problems that we currently face have been stubbornly resistant to solution, particularly unilateral solution. As we are painfully discovering, there is no way to unilaterally solve the problem of carbon dioxide buildup, which is steadily and inexorably raising the temperature around the globe…Why is it no longer possible for some world power to pull out a big stick and beat a nasty problem into submission? The answer is that it probably never was,"* (Richmond, 1993).

I argue here that the web of interdependencies between environmental mitigation efforts and the human process of policymaking has only worsened over time, and our capacity for thinking in terms of complex systems has become further challenged. As our technological capacities for modeling systems have become more robust, our epistemological boundaries have thickened. It is not the detailed computational algorithms that should dominate at the expense of causal understanding, or vice versa. Rather, we should integrate broad systems-based philosophies to achieve a multifaceted understanding of environmental policies amidst complex human-nature feedbacks.

This study highlights how identifying the function of environmental policies must be supplemented by characterizing the causal context within which the system is embedded. Several major synergies and tradeoffs associated with NBS implementation, which had hitherto been studied as a series of individual barriers (Table A.1), were revealed by combining the strengths of dynamic-, causal-, feedback, and strategy-thinking. This holistic approach was described and demonstrated using best practices among the complementary fields of PM, CLD, and FCM. Here, the initial stages of systems-thinking were used to capture system complexity from embedded stakeholder knowledge. A dynamic analysis of the resulting structure explained how the system would respond to unique policy interventions in terms of synergy and conflict. Finally, causal feedback loops were assessed according to internal strengths and overall connectivity to better understand the rationale behind observed policy effects. Such an interactive process transforms elusive systematic barriers into a broad vision of adaptive management opportunities.

Effective policy design necessitates understanding how unique interventions would propagate throughout the system to impact the end-goal. Without considering the causal chain reactions driving complex policy effects, well-intended strategies may result in stubborn environmental responses. As highlighted by Biesbroek et al. (2017), the field of environmental resilience has been largely unsuccessful in capturing and embracing the complexity of human governance feedbacks, particularly when used as an explanatory mechanism of causality. The vision for the future is that we will approach human-environmental problems as a web of interlinked connections with weighted interdependencies through the lens of systems-thinking, thereby providing a mechanism based on human reality to better understand management actions within a rapidly changing world. The framework described here 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). Rather than maintaining the confines of methodological black-boxes, this study serves as an encouragement and practical means for embracing the full spectrum of systems-thinking archetypes in environmental governance.

CRediT authorship contribution statement

Cyndi Castro: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

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

Appendix

See Table A.1.
See Fig. A.1.

Table A.1
Summary of literature review identifying key socio-institutional barriers to widespread NBS adoption and implementation.

Theme	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. Federal subsidy programs.
	Educational Opportunities	(Chaffin et al., 2016; Derkzen et al., 2017; Solheim et al., 2021; Thorne et al., 2018)	Community perceptions and understanding of NBS functionality and benefits, as well as costs. Outreach programs. Media reporting.
	Public Participation	(Baptiste et al., 2015; Bissonnette et al., 2018; Cohen-Shacham et al., 2019; Dhakal and Chevalier, 2017; Santoro et al., 2019; Wamsler et al., 2020; Zuniga-Teran et al., 2020)	Adaptive governance structure. Targeted and strategic citizen involvement in selection and planning process, funding, increasing public awareness. Neighborhood workshops. Dialogue with civil groups. Targeted media outlets.
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 to addressing climate change.
	Equitable Resilience Strategy	(Derkzen et al., 2017; Zuniga-Teran et al., 2020)	Capacitance building in vulnerable and marginalized communities with reference to NBSs.
	Co-benefits	(O'Donnell et al., 2017; Ramírez-Agudelo et al., 2020; Solheim et al., 2021)	Clear identification of co-benefits to support shared set of values and community support. Long-term focus on co-benefits.
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; Zuniga-Teran et al., 2020)	Central, singular NBS department. Integrated across sectors, separate from other utilities. Transverses multiple jurisdictions. Interagency work. Active cohesion.
	Financing	(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	(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.
	Maintainability	(Kabisch et al., 2016; Li et al., 2017; Ramírez-Agudelo et al., 2020; Thorne et al., 2018)	Regular inspections, monitoring guidelines. Cost of regular maintenance (diversified responsibility). Low-maintenance design options.
	Pilot Projects	(Li et al., 2017, 2018; Zuniga-Teran et al., 2020)	Political leadership and champions. Successful community pilot projects (tours, educational signage, press coverage).

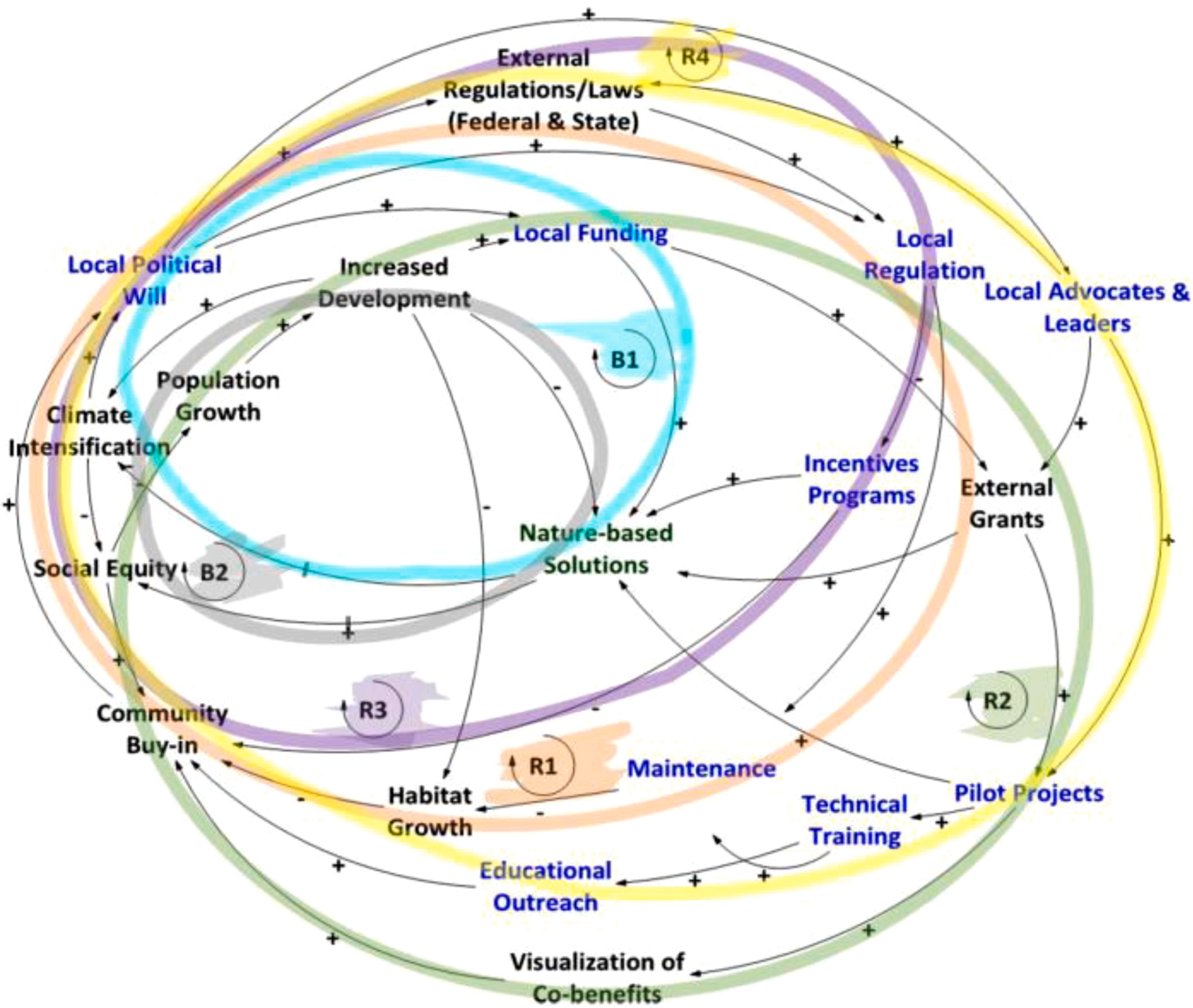

Fig. A.1. Feedback loops in causal diagram, delineated by color, presented for ease of visualization while reading and considering the impact of causal logic on policy effectiveness. Note: Color should be maintained when printed.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envsci.2022.07.001.

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