Environmental Science and Policy 136 (2022) 413–427

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Envfironmentafl Scfience and Poflficy

journal homepage: www.elsevier.com/locate/envsci

Systems-thfinkfing for envfironmentafl poflficy coherence: Stakehoflder knowfledge, fuzzy flogfic, and causafl reasonfing

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A R T I C L E I N F O

Keywords:
Partficfipatory modeflfing
Poflficy coherence
Poflficy resfistance
Fuzzy cognfitfive mappfing
Nature-based soflutfions
Causafl floop mappfing

A B S T R A C T

Envfironmentafl poflficfies are often chosen accordfing to physficafl characterfistfics that dfisregard the compflex finteractfions between decfisfion-makers, socfiety, and nature. Envfironmentafl poflficy resfistance has been fidentfified as stemmfing from such compflexfitfies, yet we flack an understandfing of how socfiafl and physficafl factors finterreflate to finform poflficy desfign. The fidentfifficatfion of synergfies and trade-offs among varfious management strategfies fis necessary to generate optfimafl resuflts from flfimfited finstfitutfionafl resources. Partficfipatory modeflfing has been used wfithfin the envfironmentafl communfity to afid decfisfion-makfing by brfingfing together dfiverse stakehoflders and deffinfing thefir shared understandfing of compflex systems, whfich are commonfly depficted by causafl feedbacks. Whfifle such approaches have fincreased awareness of system compflexfity, causafl dfiagrams often resuflt fin numerous feedback floops that are dfiffficuflt to dfisentangfle wfithout further, data-fintensfive modeflfing. When finvestfigatfing the compflexfitfies of human decfisfion-makfing, we often flack robust empfirficafl datasets to quantfify human behavfior and envfironmentafl feedbacks. Fuzzy flogfic may be used to convert quaflfitatfive reflatfionshfips finto semfi-quantfitatfive representatfions for numerficafl sfimuflatfion. However, sofle reflfiance upon computer-sfimuflated outputs may obscure our understandfing of the underflyfing system dynamfics. Therefore, the afim of thfis study fis to present and demonstrate a mfixed-methods approach for better understandfing: 1) *how* the system wfiflfl respond to unfique management strategfies, fin terms of poflficy synergfies and conflflficts, and 2) *why* the system behaves as such, accordfing to causafl feedbacks embedded wfithfin the system dynamfics. Thfis framework fis demonstrated through a case study of nature-based soflutfions and poflficymakfing fin Houston, Texas, USA.

1. Introductfion

Envfironmentafl probflems and thefir soflutfions are compflex fin nature and are often chaflflenged by socfiafl and finstfitutfionafl constructs that are not weflfl-understood. Poflficymakers strfive to make decfisfions that produce maxfimum beneffits whfifle mfinfimfizfing adverse consequences, whfich requfires fidentfifyfing and connectfing aflfl possfibfle outcomes that coufld produce synergfies and trade-offs between components. In compflex systems, such finteractfions may produce emergent behavfior, where a shfift fin one component trfiggers seflf-reguflatfing and/or dfivergent outcomes eflsewhere. When human actors finteract wfith the envfironment through pflannfing and group behavfior, socfiafl and poflfitficafl constructs adapt to the new settfing, whfich further reffines flocafl vaflues and drfives emergent phenomena. Each cycfle of thfis dynamfic system denotes a new human-nature response, whfich must be assessed accordfing to afltered characterfistfics. When confronted wfith a system of many parts, humans may try to ratfionaflfize the probflem by focusfing on seflect connectfions, thereby mfispercefivfing the overaflfl system structure and behavfior. Thfis finabfiflfity to fidentfify compflex system dynamfics often resuflts fin mfissed opportunfitfies and/or unfintended outcomes from weflfl-meanfing finterventfions, a phenomenon known as "poflficy resfistance" (Sterman, 2001).

> *"Poflficy resfistance occurs when poflficy actfions trfigger feedback from the envfironment that undermfines the poflficy and at tfimes even exacerbates the orfigfinafl probflem,"* (Ghaffarzadegan et afl., 2011).

Therefore, we cannot mfitfigate envfironmentafl fissues by sfimpfly assfignfing poflficfies that resoflve seflect barrfiers and assume the resuflts wfiflfl be proportfionaflfly reflated to the change. Instead, we must be abfle to fincorporate human agency as an endogenous component that finfluences and co-evoflves wfith the physficafl systems they seek to shape. The means

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https://dofi.org/10.1016/j.envscfi.2022.07.001
Received 8 October 2021; Received fin revfised form 14 May 2022; Accepted 1 Jufly 2022
Available online 13 July 2022

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 in a manner which reinforces progress toward the overarching goal, 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).

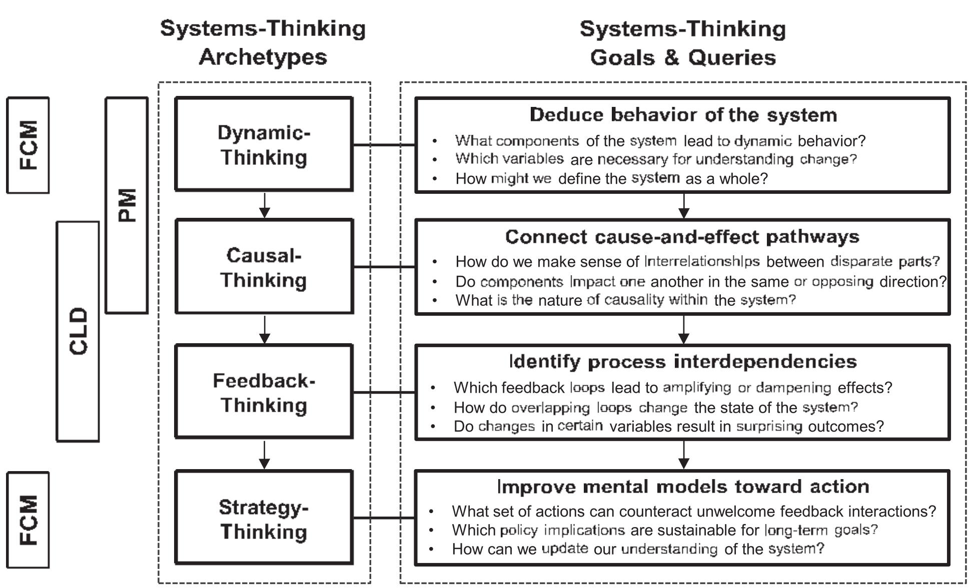


Fig. 1. General framework of how a holistic application of systems-thinking can be used to define complex, dynamic systems and assess policy effectiveness for a set of management strategies. The boxes on the left represent the common systems-thinking processes included within each of the primary archetypes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

"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 to 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 may pose inherent challenges to 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 non-linear developments emerging from within the system and their role within policymaking (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). 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 may be 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 explaining 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; Gomez 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 often been used to assess policy effectiveness. Moreover, these studies have focused on select components of the systems-thinking paradigm (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 system causality at the expense of scenario analysis, or vice versa, 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 of fuzzy cognitive maps 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 synergies and conflicts 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's (1997) call to strengthen the scientific basis of PM best-practices 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 complex relationships embedded within human cognition.

2.2. Causafl floop dfiagrams

Causafl floop dfiagrams stem from the PM process to form dynamfic hypotheses about how the system functfions. In CLDs, findfivfiduafl flfinks are marked as posfitfive (+), such that reflated varfiabfles change fin the same dfirectfion, or negatfive (-), where a change fin one varfiabfle has the opposfite fimpact on the flfinked varfiabfle. The flfinks may connect to form baflancfing floops (odd number of negatfive flfinks, counteractfing change fin the system) or refinforcfing floops (even number of negatfive flfinks, propagatfing change throughout the system). CLDs are conceptuafl fin nature and are fintended to fincrease a hoflfistfic understandfing of the causaflfity between findfivfiduafl components and sets of components. The resufltfing modefl fis cycflficafl, rather than flfinear, and expflafins non-flfinear behavfior accordfing to feedback floop finteractfions. Such finteractfions expflafin varfiabfiflfity fin the system response, whfich fis fimportant for understandfing how the dynamfic behavfior fis governed. The domfinant CLD floops finform management where key fleverage pofints are flocated and what types of actfion woufld resuflt fin the system equaflfizfing or changfing exponentfiaflfly. Poflficfies afimed at such fleverage pofints fimprove effficfiency wfithfin the system and heflp us to better manage emergent behavfior (Sternam, 2002).

2.3. Fuzzy cognfitfive mappfing

Whfifle CLD's provfide finformatfion regardfing the dfirectfion of centrafl reflatfionshfips of the system, an understandfing of how the system wfiflfl pflay out over tfime fis necessary for decfisfion-makfing. For thfis, fuzzy cognfitfive maps (FCMs) provfide a semfi-quantfitatfive basfis for sfimuflatfing compflex dynamfics accordfing to the system structure and the strengths of varfiabfle reflatfionshfips. FCMs parameterfize system reflatfionshfips accordfing to fuzzy flogfic by transflatfing quaflfitatfive descrfiptfions of strength (e.g., flow, medfium hfigh) to semfi-quantfitatfive wefights between 1.00 (strong negatfive causaflfity) and + 1.00 (strong posfitfive causaflfity) (Gray et afl., 2014). Mathematficafl pafirwfise assocfiatfions between system varfiabfles are then summarfized wfithfin a square adjacency matrfix, whfich may be sfimuflated to better understand current and projected system states (Ozesmfi and Ozesmfi, 2004). The dynamfics of FCM modefls are specfiffied by state vectors, fin whfich the state vector of one varfiabfle depends on the state vectors of afflfl other connected varfiabfles over tfime.

To sfimuflate the FCM network, varfiabfles are denoted as equfivaflent to neurons that can be actfivated at the onset of the sfimuflatfion whfifle aflso adoptfing fin-between states. An actfivatfion vaflue of + 1.00 findficates the varfiabfle fis strengthened to the maxfimum possfibfle wefight (known as "cflampfing"), thereby finfluencfing afflfl connected varfiabfles throughout the sfimuflatfion. Conversefly, an actfivatfion vaflue of 0 means the varfiabfle does not change at the on-set of sfimuflatfion and fis onfly finfluenced by the dynamfics of causafl connectfions. The actfivated varfiabfle state fis mufltfipflfied by the adjacency matrfix at each tfime step, whfich propagates throughout the sfimuflatfion accordfing to causaflfity, thereby spreadfing fin a non-flfinear fashfion untfifl the system reaches equfiflfibrfium (Jetter and Schwefinfort, 2011). When appflfied to poflficymakfing, a serfies of artfifficfiafl scenarfios are sfimuflated by "cflampfing" seflect management varfiabfles and comparfing end-state vectors agafinst a baseflfine scenarfio. The extent of change between the actfivated and the baseflfine scenarfio projects how the system wfiflfl respond to unfique poflficfies accordfing to dynamfic finteractfions wfithfin the modefl.

2.4. Identfifyfing synergfies & confflficts

Poflficy anaflysfis descrfibes the sensfitfivfity of the modefl to human finteractfion. By aflterfing one (or more) of the system varfiabfles and assessfing the resufltfing outcomes, patterns begfin to emerge that reveafl whfich poflficfies woufld flead to optfimafl (or sub-optfimafl) resuflts (Barflas, 2002). Here, FCM-based scenarfio modeflfing fis used to sfimuflate NBS management strategfies and assess changes to the state of NBS fimpflementatfion. Specfifficaflfly, end-state vectors for varfious poflficy combfinatfions are compared to fidentfify areas of synergy or confflfict, as descrfibed by Eqs. 1-2.

Poflficy synergy occurs when a strategy produces better output than the sum of any findfivfiduafl components comprfisfing the gfiven cohort, deffined by

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

where ΔS_k descrfibes the percent change of the end-state vector for the system goafl varfiabfle wfithfin management strategy (k), j fis the number of unfique poflficfies befing combfined wfithfin strategy k to a maxfimum of n totafl poflficfies. [Note: j fis wfithfin the set of naturafl fintegers (A) that sum to n (e.g., fif $n = 6$, $j = \{1, 5\}|\{2, 4\}|\{3, 3\}|\{2, 2, 2\}|\{1, 2, 3\}$, etc.)].

Poflficy confflfict occurs when addfing any extra components to the strategy resuflts fin fless output than had the components not been combfined, such that

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

where j fis wfithfin the set of naturafl fintegers (B) that sum to be fless than n. The flogficafl *or* operator ($\vee$) means that any combfinatfion of ΔS_{kj} whfich fis greater than ΔS_{kn} woufld resuflt fin poflficy confflfict (e.g., fif $n = 4$, confflfict occurs for any $\Delta S_{kj} > \Delta S_{k4}$, where $j = \{1\}|\{2\}|\{3\}|\{1, 1\}|\{1, 2\}|\{2, 1\}$, etc.).

2.5. Expflafinfing poflficy coherence

Areas of synergy and confflfict may be compared to the strengths of finternafl feedback floops to better understand the poflficy fimpflficatfions of embedded causafl flogfic.

Here, the wefighted strengths of causafl feedback floops are deffined by

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

where w_f descrfibes the average wefighted strength of each feedback floop f at sfimuflatfion tfime $t = 0$, w_{ij} fis the fuzzy strength between varfiabfle i and j, and M fis the totafl number of unfique connectfions wfithfin the feedback floop. The floop strength fis assfigned a poflarfity of '+ ' for refinforcfing and '-' for baflancfing.

3. Case study: nature-based soflutfions

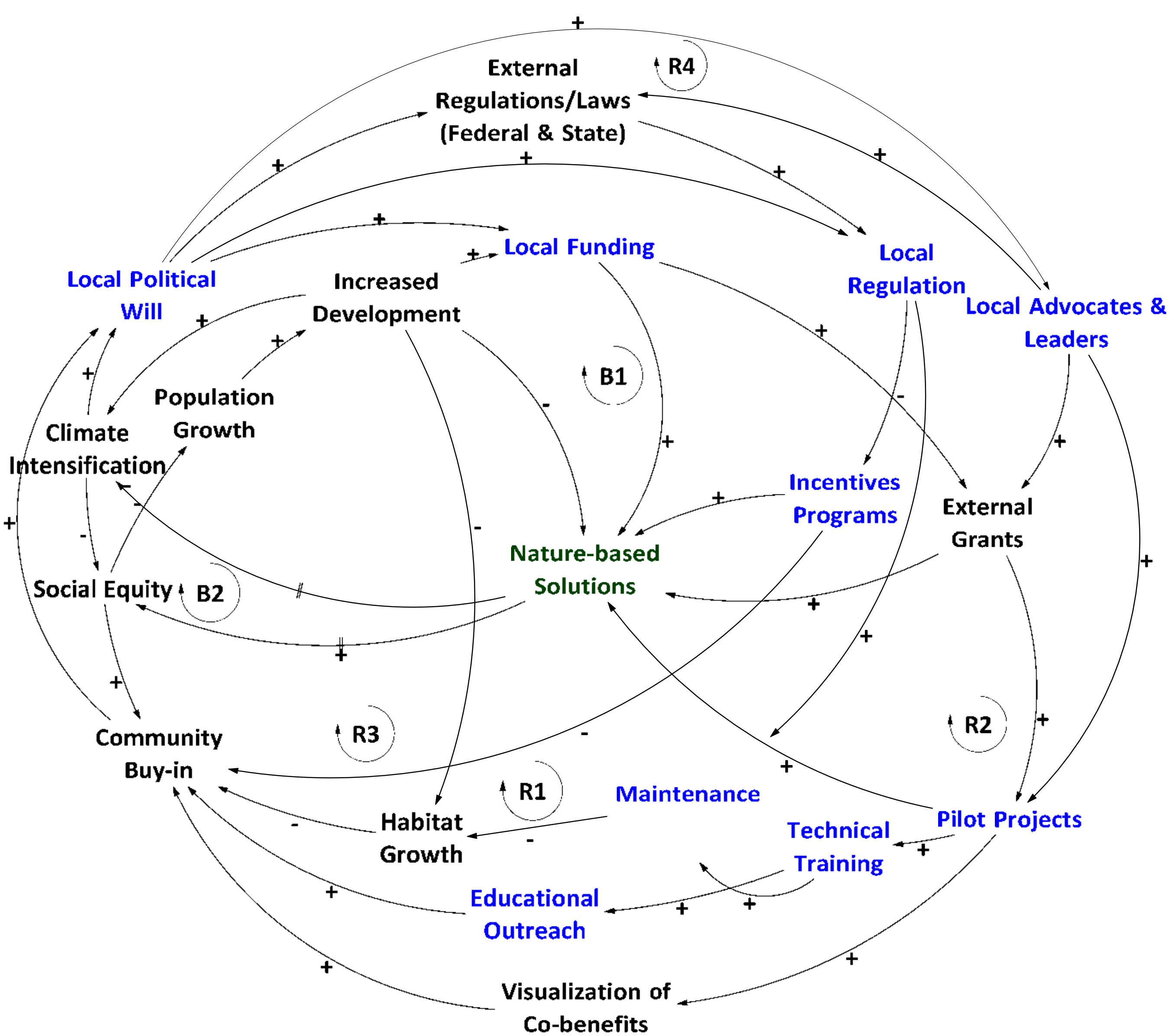
To demonstrate the methodoflogy descrfibed fin **Sect. 2**, a case study was conducted fin Houston, TX, USA regardfing poflficfies for fimproved adoptfion of nature-based soflutfions (NBSs). As cflfimate change and urban densfifficatfion contfinue to rfise, tradfitfionafl stormwater systems are befing chaflflenged by flfimfited conveyance capacfitance and expensfive mfitfigatfion strategfies (ASCE, 2020). Many fflood-prone communfitfies, such as Houston, are consfiderfing soft-scafle soflutfions to compflement drafinage networks by emuflatfing naturafl watershed processes and flfimfitfing the amount of stormwater runoff enterfing the system (Demuzere et afl., 2014). In addfitfion to mfitfigatfing stormwater, NBSs have been assocfiated wfith numerous co-beneffits, fincfludfing fimproved mentafl and physficafl heaflth, socfiafl vuflnerabfiflfity, economfic prosperfity, afir and water quaflfity, temperature reguflatfion, and ecosystem conservatfion. Aflthough such beneffits have been broadfly observed throughout the flfiterature (see Tabfle S.1), wfidespread adoptfion of NBS has remafined stunted due to socfio-finstfitutfionafl compflexfitfies assocfiated wfith envfironmentafl poflficy-makfing.

For exampfle, observatfionafl case studfies have fidentfiffied severafl key chaflflenges to NBS uptake, fincfludfing communfity perceptfions and understandfing of NBS functfionaflfity (Baptfiste et afl., 2015), cuflturafl vaflues pertafinfing to rfisk and/or change, (Derkzen et afl., 2017), and finstfitutfionafl frameworks assocfiated wfith fundfing, reguflatfions, fleadershfip, technficafl desfign, and mafintenance (Soflhefim et afl., 2021; Zunfiga-Teran et afl., 2020) (summarfized fin Tabfle A.1). Whfifle these barrfiers have been studfied as fisoflated events, we flack a generafl understandfing of how such factors operate hoflfistficaflfly to finffluence one another. A recent workshop conducted by the Unfited Natfions Envfironment Programme (UNEP) Intergovernmentafl Panefl on Cflfimate Change (IPCC) emphasfized that compflexfitfies wfithfin mufltfi-functfionafl poflficymakfing and thefir physficafl-socfiafl feedbacks are key fimpedfiments to NBS uptake. The IPCC recommended a shfift toward co-produced knowfledge between practfitfioners and researchers to overcome such fimpflementatfion chaflflenges (Frantzeskakfi et afl., 2019). An exampfle of co-produced knowfledge and systems-thfinkfing wfithfin the reaflm of NBS fis demonstrated by the fofllowfing case study.

3.1. Eflficfitfing stakehoflder knowfledge

A vfirtuafl workshop was hefld to capture the mentafl modefls of experts who had been finvoflved wfith NBS fimpflementatfion efforts fin Houston, TX, USA (Text S.1, Tabfle S.2). The PM workshop was facfiflfitated by gufidfing the stakehoflder group through a serfies of finteractfive scrfipts for understandfing system causaflfity, deffinfing key reflatfionshfips, fidentfifyfing feedback strengths, and reflflectfing on modefl-based finsfights (Text S.2). Durfing the PM process, stakehoflders were asked to consfider how unfique factors have flfimfited or advanced NBS efforts accordfing to thefir flfived experfiences. Throughout the semfi-structured process, partficfipants fidentfiffied numerous causafl factors assocfiated wfith NBS fimpflementatfion, whfich were documented fin reafl-tfime and grouped accordfing to key socfio-finstfitutfionafl themes (e.g., chaflflenges and barrfiers, management opportunfitfies, and exogenous factors) (Ffig. S.1, Tabfle S.3).

The facfiflfitator seflected severafl varfiabfles from the eflficfitatfion exercfise and drew them as nodes wfithfin a web-based whfiteboard. Sampfle causafl reflatfionshfips and feedback floops were descrfibed and demonstrated vfisuaflfly wfithfin the shared finterface. The partficfipants were asked to descrfibe thefir understandfing of causafl feedbacks between the dfifferent eflements, whfich fostered robust dfiscussfions of the underflyfing system dynamfics. Indfivfiduafl stakehoflders dfiscussed thefir finterpretatfion of



Ffig. 2. Stakehoflder-derfived causafl floop dfiagram depfictfing socfiafl-finstfitutfionafl factors finvoflved wfith fimpflementatfion of nature-based soflutfions. Bflue = management opportunfitfies, wfithfin the scope of stakehoflder finffluence. Bflack = exogenous varfiabfles, outsfide the scope of stakehoflder finffluence. Green = system goafl varfiabfle. Poflarfity of feedback floops fis findficated by '+ ' for posfitfive (same-dfirectfion causatfion) and '-' for negatfive (opposfite-dfirectfion causatfion). Refinforcfing and baflancfing feedback floops are denoted by dfirectfion and nomencflature 'R' and 'B', respectfivefly. Note: Coflor shoufld be mafintafined when prfinted.

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 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 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.4.

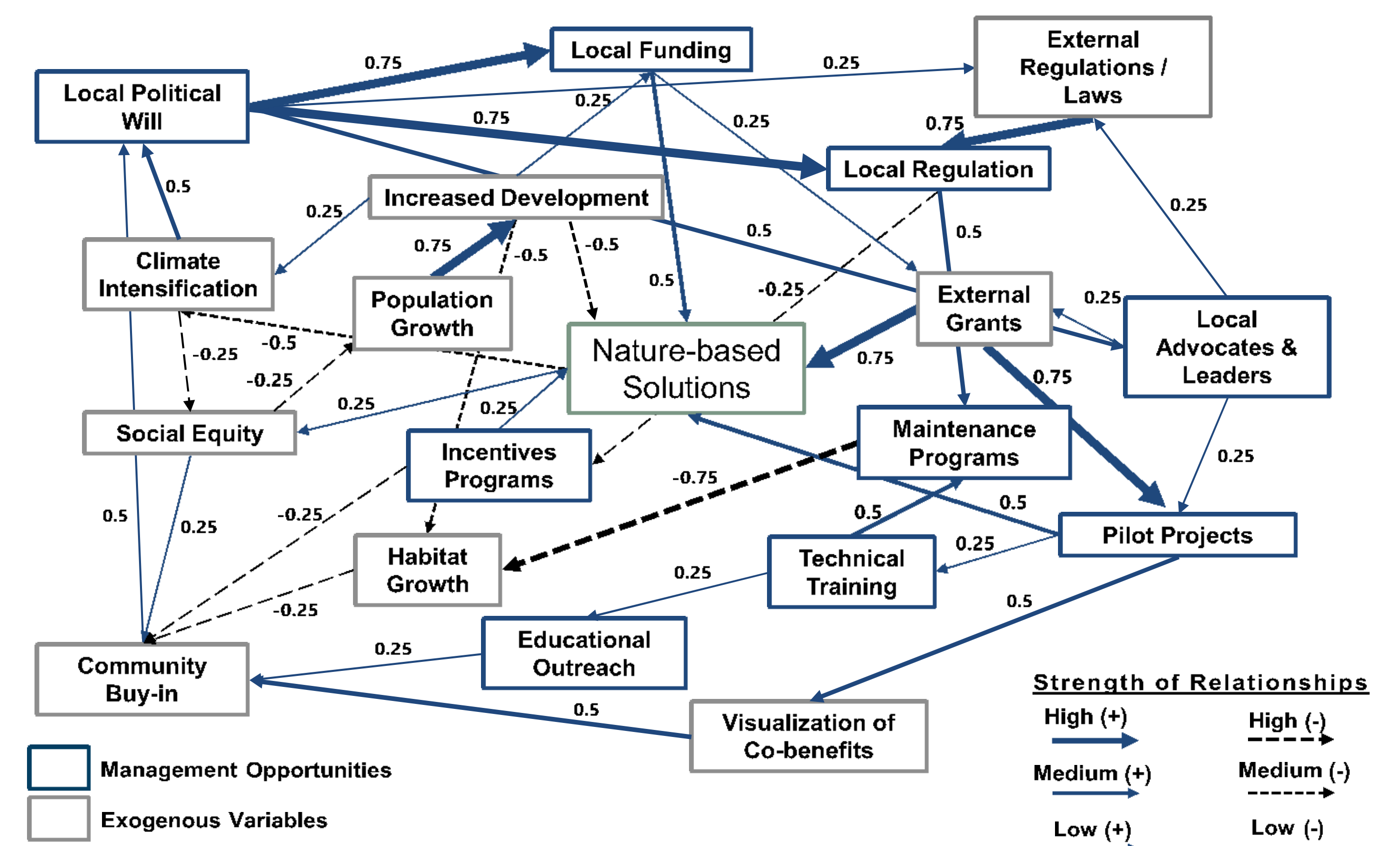
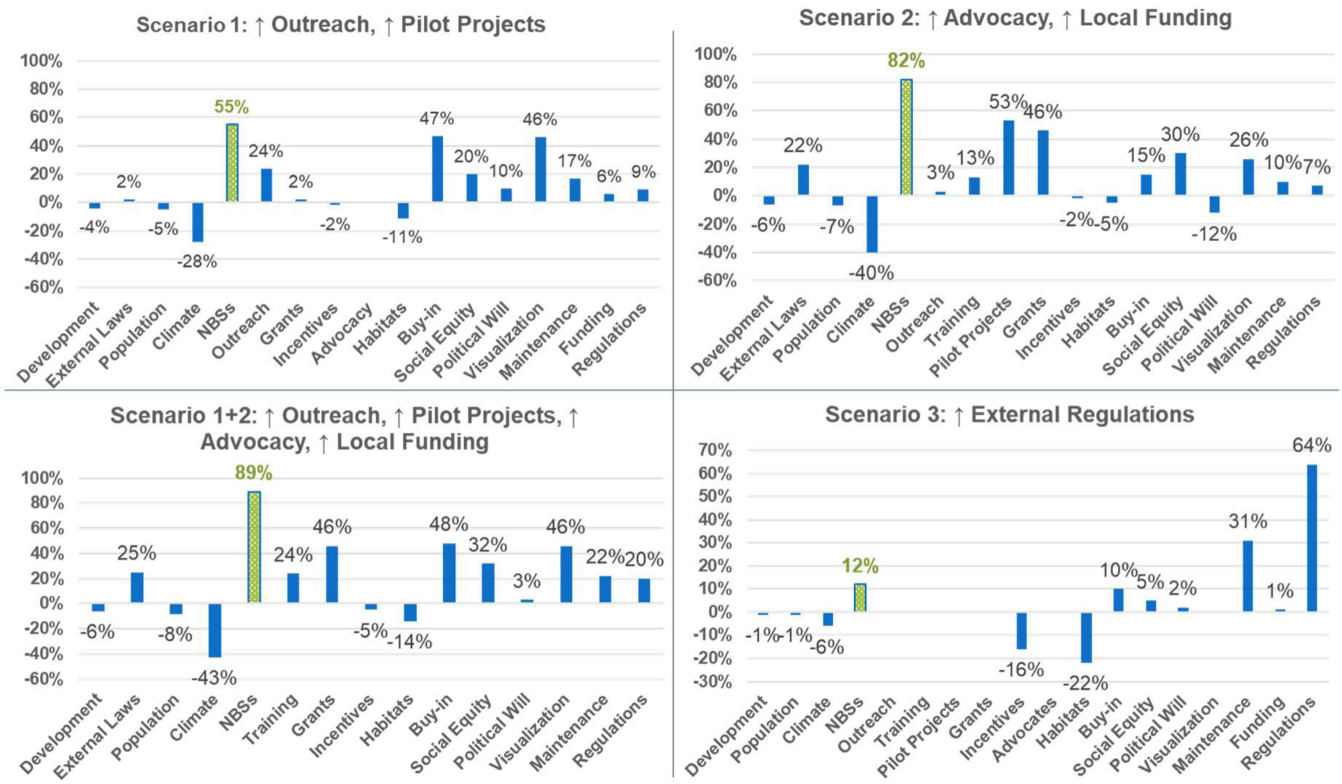


Fig. 3. Fuzzy cognitive map, as elicited by the stakeholder group for describing NBS socio-institutional challenges as either management opportunities (within the scope of stakeholder influence) or exogenous variables (outside the scope of stakeholder influence). Blue arrows = '+' polarity. Black, dashed 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.



Ffig. 4. Scenarfio output from *Mentafl Modefler* (FCM-based sfimuflatfion software), where the poflficy varfiabfle(s) flfisted fin each chart tfitfle were actfivated through cflampfing to a vaflue of + 1.00, and changes fin each varfiabfle state vector between the status quo and the ffinafl dynamfic sfimuflatfion were graphed as a reflatfive percentage (ΔS_{NBS}). The shfifts fin state vector magnfitude for nature-based soflutfions, whfich were the goafl varfiabfle for thfis system, are shown fin green.

3.3. Sfimuflatfing management strategfies

The wefighted FCM was used to sfimuflate varfious "what-fif" management strategfies (where a strategy comprfises one or more findfivfiduafl poflficfies) to better understand how a change fin flocafl poflficy woufld fimpact the reflatfive state of the NBS goafl varfiabfle. Out of 19 totafl system varfiabfles, the FCM contafined 9 management opportunfitfies whfich were deemed to be wfithfin the stakehoflders' sphere of finffluence (fi.e., Educatfionafl Outreach (EO), Technficafl Trafinfing (TT), Pfiflot Projects (PP), Incentfives Programs (IP), Advocacy and Leadershfip (AL), Poflfitficafl Wfiflfl (PW), Mafintenance (MT), Locafl Fundfing (FU), Locafl Reguflatfions (RE)). From these varfiabfles, 129 fuzzy scenarfios were fidentfiffied by assumfing the stakehoflders woufld fimpflement efither a sfingfle poflficy strategy (n = 9), a strategy combfinfing two poflficfies (n = 36), or a strategy combfinfing three poflficfies (n = 84).

The sfimuflatfions fin *Mentafl Modefler* use the adjacency matrfix (Tabfle S.4) to represent the strengths of finterconnectfions and state vectors to characterfize the degree of varfiabfle change once a scenarfio fis actfivated. As such, the modeflfing sufite quantfiffies dynamfic finteractfions between system components for dfiscrete tfime-steps untfifl the system converges to equfiflfibrfium by appflyfing formaflfized actfivatfion rufles and transformatfion functfions to the adjacency matrfix. The specfiffic mathematficafl functfions used wfithfin *Mentafl Modefler* fincflude the Kosko's actfivatfion rufle and the hyperboflfic transformatfion functfion, whfich are further detafifled by Gray et afl., (2015, 2013). After the system stabfiflfizes (typficaflfly before 10 fiteratfions), changes fin the end-state vectors are output as a reflatfive percentage. Ffigure 4 demonstrates how actfivatfing a unfique set of poflficy nodes may fimpact a varfiety of state shfifts fin the remafinfing varfiabfles, both posfitfive and negatfive, accordfing to the modefl structure and the system dynamfics.

Areas of poflficy synergy and confflfict were then caflcuflated from the sfimuflatfion outputs (per Eqs. 1–2) to fidentfify whfich combfinatfions of management strategy produced cohesfive or resfistant outcomes. The strengths of the refinforcfing and baflancfing feedback floops were aflso caflcuflated (per Eq. 3) to better understand the observed poflficy effects fin accordance wfith the system's causafl structure.

4. Results

4.1. Characterfizfing system causaflfity

The stakehoflder workshop reveafled 19 unfique varfiabfles and 37 causafl flfinks assocfiated wfith NBS fimpflementatfion and management fin Houston, TX. These resuflts corresponded weflfl wfith the average number of varfiabfles (n = 23) and connectfions (n = 37) observed fin socfioenvfironmentafl systems, accordfing to a meta-study by Ozesmfi and Ozesmfi (2004). Accordfing to *Vensfim*, the CLD varfiabfles connected to form 97 unfique feedback floops. A key sampflfing of four refinforcfing floops and two baflancfing floops were chosen to demonstrate the systems-thfinkfing framework (Ffig. A.1). Durfing the PM sessfion, the stakehoflders were asked to deffine the fuzzy strengths of causafl connectfivfity between system varfiabfles, whfich were used to determfine the average wefightfing of each feedback floop at the onset of FCM-based sfimuflatfion (Eq. 3). Tabfle 1 summarfizes the poflarfity and wefighted strength for each feedback floop. Here, refinforcfing floop R1 was noted as the "Mafintenance Loop", where fimproved mafintenance from flocafl reguflatfions woufld reduce habfitat over-growth and fimprove communfity buy-fin of NBS technoflogfies, drfivfing poflfitficafl wfiflfl and flocafl reguflatfions. Refinforcfing floop R2, the "Fundfing Loop", was fidentfiffied as an opportunfity to fincrease NBSs by usfing flocafl funds to fimpflement more pfiflot projects, thereby enhancfing vfisuaflfizatfion of co-beneffits and strengthenfing communfity buy-fin. The refinforcfing floop R3, "Communfity Loop", descrfibes the generafl stakehoflder beflfief that enhanced externafl reguflatfions woufld drfive flocafl reguflatfion, negatfing the need for vofluntary fincentfives programs. Thfis, fin turn, woufld drfive flocafl poflfitficafl wfiflfl and trfigger addfitfionafl finffluence of federafl and state reguflatfions. Refinforcfing

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	Political Will →(+0.75) Local Regulation →(+0.50) Maintenance → (-0.75) Habitat Growth →(-0.25) Community Buy-in →(+0.50) Political Will	0.35
R2	Political Will →(+0.75) Local Funding →(+0.25) External Grants →(+0.75) Pilot Projects →(+0.50) Visualization of Co-benefits →(+0.50) Community Buy-in →(+0.50) Political Will	0.54
R3	Political Will →(+0.25) External Regulation →(+0.75) Local Regulation →(-0.25) Incentives Programs →(-0.25) Community Buy-in →(+0.50) Political Will	0.40
R4	Political Will →(+0.50) Local Advocates →(+0.25) Pilot Projects →(+0.25) Technical Training →(+0.25) Educational Outreach →(+0.25) Community Buy-in →(+0.50) Political Will	0.33
B1	Political Will →(+0.75) Local Funding →(+0.50) Nature-based Solutions →(-0.50) Climate Intensification →(+0.50) Local Political Will	- 0.56
B2	Social Equity →(-0.25) Population Growth →(+0.75) Increased Development →(+0.25) Local Funding →(+0.25) Nature-based Solutions →(+0.50) Social Equity	- 0.40

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 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 slightly less output than had they been implemented separately. The shift in NBS state-vector for strategy AL-FU, without PW, 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

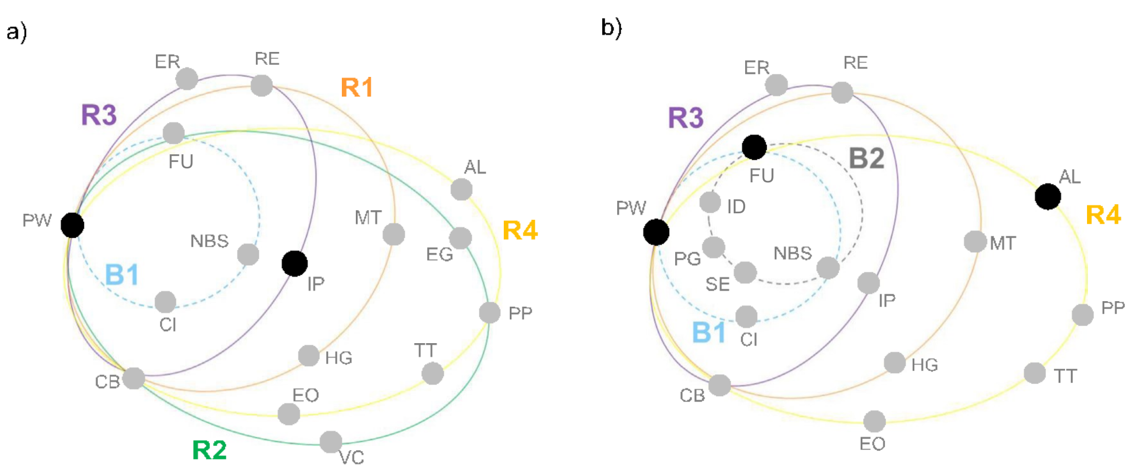


Fig. 5. Illustration of causal feedback loop interactions associated with activation of select policy variables (black), and all associated causal variables (grey) for **a)** policy synergy and **b)** policy conflict. [Educational Outreach = EO, Technical Training = TT, Pilot Projects = PP, Incentives 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 =ID]. The reinforcing (R) and balancing (B) loops correspond to color-coded nomenclature in Fig. A.1.

Table 2
Fuzzy cognfitfive mappfing-based scenarfio output used to understand poflficy effectfiveness on the ffinafl state change ΔS_k of nature-based soflutfions. k = nomencflature of each strategy. [Educatfionafl Outreach = EO, Technficafl Trafinfing = TT, Pfiflot Projects = PP, Incentfives Programs = IP, Advocacy and Leadershfip = AL, Poflfitficafl Wfiflfl = PW, Mafintenance = MT, Locafl Fundfing = FU, Locafl Reguflatfions = 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%		

expflored to assess the finffluence of feedback floops on poflficy coherence. In consfiderfing the synergy between IP and PW, we may flocate each poflficy varfiabfle wfithfin the composfite CLD and examfine thefir assocfiated feedback floops. As demonstrated fin Ffig. 5**a**, poflfitficafl wfiflfl (PW) fis flocated at the confluence of ffive feedback floops, each wfith unfique strengths and poflarfitfies (R1, R2, R3, R4, B1). Incentfives programs (IP) are onfly flocated on floop R3. Sfince R3 fis connected to the same feedback floops as PW, vfia the PW node, actfivatfion of both poflficfies generates a very strong response from aflfl four refinforcfing floops fin the dfiagram. Even though baflancfing floop B1 fis trfigged fin thfis scenarfio, the combfinatfion of refinforcfing effects fis much stronger than the equaflfizfing effects of B1 (e.g., $\sum_{fi=1}^{4} w_{Rfi} \gg w_{B1}$). In other words, flocafl actfivfism produces a synergfistfic effect that propagates a strong, posfitfive trajectory throughout the system through fimproved mafintenance, fundfing, communfity buy-fin, and fleadershfip. Once actfivated, these floops are not easfifly dampened by the baflancfing effects of the cflfimate floop.

In consfiderfing the confflfictfing nature of AL-PW-FU, we may observe the feedback floops demonstrated fin Ffig. 5**b**. Actfivatfion of PW exhfibfits the same effects as descrfibed prevfiousfly. Actfivatfion of AL trfiggers floop R4, whfich when combfined wfith PW, resuflts fin a strong refinforcfing effect. However, when node FU fis actfivated, both baflancfing floops B1 and B2 are trfiggered, thereby dampenfing the system trajectory. Accordfing to the stakehoflders, FU was presumed to have a posfitfive causafl assocfiatfion wfith flocafl deveflopment and popuflatfion growth, whfich negatfivefly fimpact urban greenfing. Sfince floop R4 fis reflatfivefly weak, actfivatfion of AL does not offset these baflancfing effects. Whfifle thfis strategy does not shfift the system finto a negatfive state (fi.e., poflficy resfistance), fit coufld be argued that addfitfionafl PW aflongsfide AL-FU fis not an effficfient use of resources.

Addfitfionafl finsfights may be derfived by rankfing the NBS end-state vectors for aflfl strategfies and notfing the occurrence of specfiffic poflficfies (Tabfle 3). Varfiabfles PP, PW, and FU are noted wfithfin many hfigh-effficfiency strategfies (fi.e., upper quartfile). Both PP and PW are flocated at the confluence of severafl strong refinforcfing floops, whfich expflafins why they are assocfiated wfith greater NBS fimpact fin the system. FU fis a component of both the strong baflancfing floops B1-B2 and the strong refinforcfing floop R2, whfich may have trended the system toward equfiflfibrfium had there been no other dynamfic forces finvoflved. However, floop R2 trfiggers severafl other refinforcfing floops, thereby potentfiaflfly ampflfifyfing systematfic change, dependfing on the actfivfity of other assocfiated varfiabfles. Other system varfiabfles that finteracted wfith floop B1, but whfich dfid not have strong refinforcements to counteract the baflancfing forces, showcased fless favorabfle outcomes. Conversefly, varfiabfles TT, MT, and EO tended to exhfibfit weak effficfiencfies when combfined wfith other poflficy optfions. An assessment of the assocfiated causafl structures demonstrated how these varfiabfles are each flocated on onfly one feedback floop, thereby trfiggerfing fless change and momentum fin the overaflfl system trajectory than those varfiabfles that are fleveraged at the fintersectfion of many overflappfing floops. Whfifle such manuafl finterpretatfions of aflfl poflficy combfinatfions and feedback floops wfithfin the system woufld qufickfly become burdensome, the approach presented here provfides a rapfid vfisuafl assessment of how strategfies may finteract wfithfin the system

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, Local Funding = FU, Local 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%

dynamics to produce synergies or conflicts according to embedded causality. When combined with the quantitative strengths of scenario-building, we are able to gain a fuller picture of policy effects associated with human-nature systems.

5. Methodological limitations

Several limitations to this methodology 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 modelling. A deeper investigation of FCM-based modelling, activation rules, and inference capabilities is noted by Napoles et al. (2018) and Papageorgiou et al. (2018). Using FCM to 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* (Ozesmi and Ozesmi, 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 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%($\Delta S_{EO\ PW\ RE}$) < 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 2). 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. Figure 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, which had a strong positive impact on 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), environmental science has been largely unsuccessful in capturing 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 underlying 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 author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

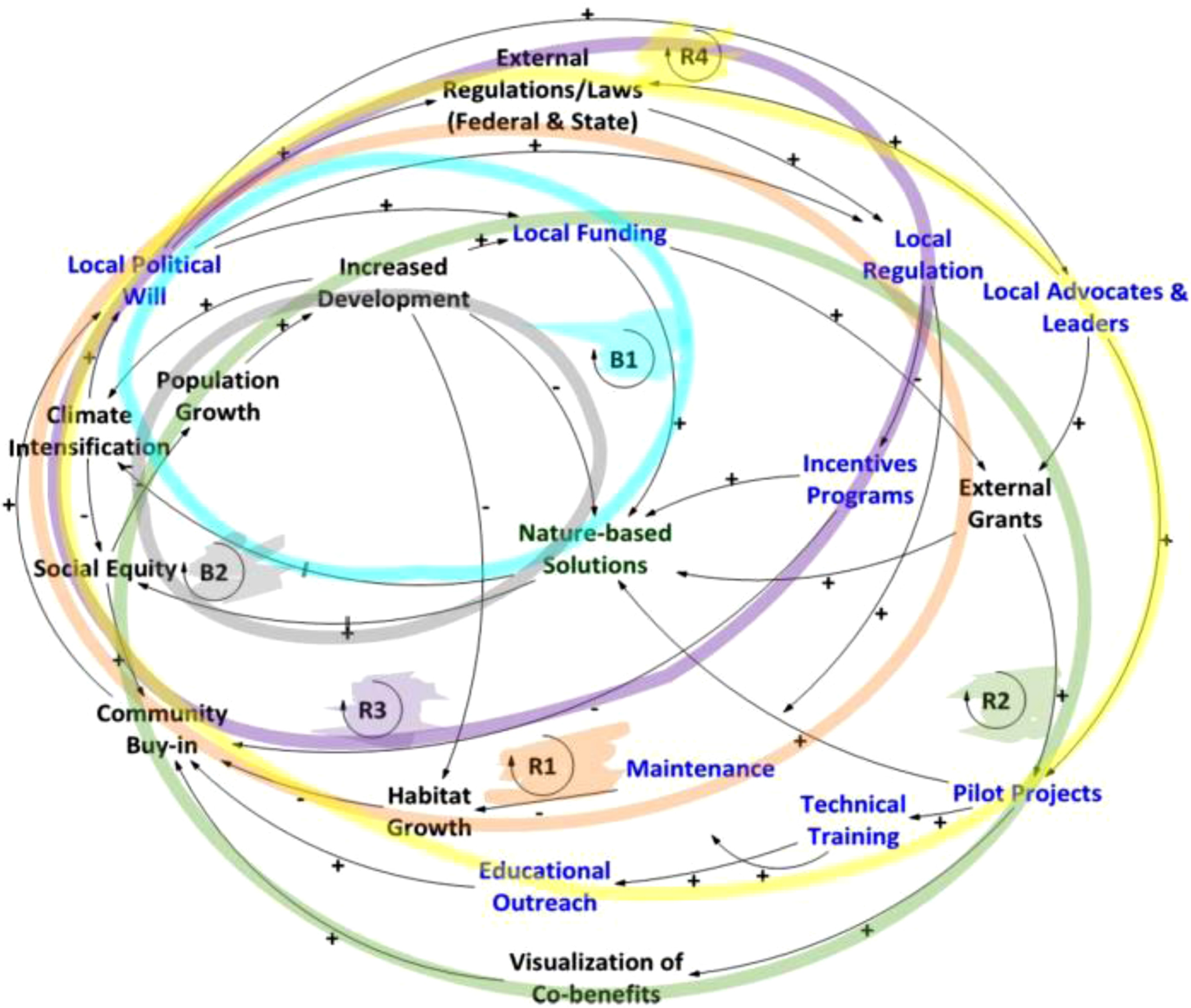
This material is based upon work supported by the National Science Foundation under Award No. 2052598.

Appendix

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

Table A.1
Summary of flfiterature revfiew fidentfifyfing key socfio-finstfitutfionafl barrfiers to wfidespread NBS adoptfion and fimpflementatfion.

Theme	Varfiable	References	Key Consfideratfions
Communfity Buy-fin	Economfic Incentfives	(Baptfiste et afl., 2015; Tayouga and Gagnè, 2016; Vogefl et afl., 2015)	Subsfidfies, grants, floans, fee reductfions. Incorporated finto flocafl deveflopment pflants. Drafinage tax/fee reductfion for findfivfiduafl resfidents. Federafl subsfidy programs.
	Educatfionafl Opportunfitfies	(Chafffin et afl., 2016; Derkzen et afl., 2017; Soflhefim et afl., 2021; Thorne et afl., 2018)	Communfity perceptfions and understandfing of NBS functfionaflfity and beneffits, as weflfl as costs. Outreach programs. Medfia reportfing.
	Pubflfic Partficfipatfion	(Baptfiste et afl., 2015; Bfissonnette et afl., 2018; Cohen-Shacham et afl., 2019; Dhakafl and Chevaflfier, 2017; Santoro et afl., 2019; Wamsfler et afl., 2020; Zunfiga-Teran et afl., 2020)	Adaptfive governance structure. Targeted and strategfic cfitfizen finvoflvement fin seflectfion and pflannfing process, fundfing, fincreasfing pubflfic awareness. Nefighborhood workshops. Dfiaflogue wfith cfivfifl groups. Targeted medfia outflets.
Socfial Culture	Cuflturafl Vaflues	(Derkzen et afl., 2017; Soflhefim et afl., 2021; Thorne et afl., 2018)	Tradfitfionafl versus progressfive engfineerfing cuflture. Pubflfic perceptfion shfift. Fear of percefived rfisk to change. Lack of sense of urgency to addressfing cflfimate change.
	Equfitabfle Resfiflfience Strategy	(Derkzen et afl., 2017; Zunfiga-Teran et afl., 2020)	Capacfitance bufifldfing fin vuflnerabfle and margfinaflfized communfitfies wfith reference to NBSs.
	Co-beneffits	(O'Donneflfl et afl., 2017; Ramírez-Agudeflo et afl., 2020; Soflhefim et afl., 2021)	Cflear fidentfifficatfion of co-beneffits to support shared set of vaflues and communfity support. Long-term focus on co-beneffits.
Instfitutfional Characterfistfics	Fragmentatfion	(Chafffin et afl., 2016; Efllfis and Lundy, 2016; Kabfisch et afl., 2016; Ramírez-Agudeflo et afl., 2020; Soflhefim et afl., 2021; Vasquez et afl., 2016; Wamsfler et afl., 2020; Zunfiga-Teran et afl., 2020)	Centrafl, sfinguflar NBS department. Integrated across sectors, separate from other utfiflfitfies. Transverses mufltfipfle jurfisdfictfions. Interagency work. Actfive cohesfion.
	Ffinancfing	(Lfi et afl., 2017; McRae, 2016; O'Donneflfl et afl., 2017; Soflhefim et afl., 2021; Thorne et afl., 2018; Zunfiga-Teran et afl., 2020)	Understandfing cost comparfison to grey-finfrastructure. Quantfifficatfion of co-beneffits. Combfined fundfing sources. Adequate economfic resources. Competfing prfiorfitfies.
	Reguflatory Frameworks	(Dhakafl and Chevaflfier, 2016; Gersonfius et afl., 2016; Levy et afl., 2014; O'Donneflfl et afl., 2017; Sarabfi et afl., 2020; Soflhefim et afl., 2021)	Less strfingent than grey-water, fimproves costs and fimpflementatfion. Deffined flegafl standards. Threshoflds to trfigger NBS stormwater management. Confusfion/confflfictfing provfisfions. Reguflatfions regardfing flong-term mafintenance requfirements.
Engfineerfing & Mafintenance	Desfign Standards	(Kronenberg, 2015; Soflhefim et afl., 2021; Zunfiga-Teran et afl., 2020)	Uncertafintfies regardfing how NBSs work flocaflfly. Technficafl manuafls. Spatfiafl pflannfing gufideflfines.
	Technficafl Experfience	(Lfi et afl., 2017; O'Donneflfl et afl., 2017; Soflhefim et afl., 2021; Wamsfler et afl., 2020; Zunfiga-Teran et afl., 2020)	Hfistory of past project success. Certfiffied expertfise. Workshops and trafinfings. Staff turnover of NBS expertfise.
	Mafintafinabfiflfity	(Kabfisch et afl., 2016; Lfi et afl., 2017; Ramírez-Agudeflo et afl., 2020; Thorne et afl., 2018)	Reguflar finspectfions, monfitorfing gufideflfines. Cost of reguflar mafintenance (dfiversfiffied responsfibfiflfity). Low-mafintenance desfign optfions.
	Pfiflot Projects	(Lfi et afl., 2017, 2018; Zunfiga-Teran et afl., 2020)	Poflfitficafl fleadershfip and champfions. Successfufl communfity pfiflot projects (tours, educatfionafl sfignage, press coverage).



Ffig. A.1. Feedback floops fin causafl dfiagram, deflfineated by coflor, presented for ease of vfisuaflfizatfion whfifle readfing and consfiderfing the fimpact of causafl flogfic on poflficy effectfiveness. Note: Coflor shoufld be mafintafined when prfinted.

Appendfix A. Supportfing finformatfion

Suppflementary data assocfiated wfith thfis artficfle can be found fin the onflfine versfion at doi:10.1016/j.envscfi.2022.07.001.

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