ARTICLE OPEN

Check for updates

Urbanized knowledge syndrome—erosion of diversity and systems thinking in urbanites' mental models

Payam Aminpour[1,2]✉, Steven A. Gray[3], Michael W. Beck[4], Kelsi L. Furman[5], Ismini Tsakiri[5], Rachel K. Gittman[6], Jonathan H. Grabowski[5], Jennifer Helgeson[2], Lauren Josephs[7], Matthias Ruth[8] and Steven B. Scyphers[5]

Coastal ecosystems nearby human societies collectively shape complex social-ecological systems (SESs). These ecosystems support high levels of ecological biodiversity while providing resources and services to humans. However, shoreline armoring, land transformation, and urban homogenization across urbanized coastal areas may degrade natural ecosystems and alter how humans and nature are connected. We hypothesize that these alterations extend to residents' knowledge of SESs. We explore evidence of such cognitive outcomes in graphical mental models of more than 1350 coastal residents across eight states in the Northeast United States. Our results revealed that, in more urbanized areas, residents' mental models underrepresented complex interdependence between humans and natural components, indicating limited systems thinking. Additionally, urbanization and shoreline armoring were associated with homogenization of mental models. We refer to these results as Urbanized Knowledge Syndrome (UKS). Importantly, respondents with more symptoms of UKS were less likely to self-report adoption of pro-environmental behaviors. These results indicate a potential societal-level erosion of ecological knowledge associated with urbanization in the same way more urbanized areas are associated with diminishing ecological function. Thus, diagnosing and treating UKS is an essential component of urban sustainability.

npj Urban Sustainability (2022)2:11 ; https://doi.org/10.1038/s42949-022-00054-0

INTRODUCTION

The world's population is rapidly urbanizing, particularly along coastlines, where population density is now three times higher than the global average[1,2]. According to the National Oceanic and Atmospheric Administration (NOAA), almost 40% of the United States (U.S.) population resides in coastal zones with population density being over five times greater in coastal shoreline counties than the national average. As a result, human encroachment on coastal ecosystems is significantly modifying natural landscapes and reducing intact coastal habitat. Along densely populated coastlines, residential development often involves unsustainable land-use planning and armoring of shorelines, where natural habitats such as saltmarshes, mangroves, seagrasses and oyster reefs, are replaced with artificial structures, including vertical bulkheads, seawalls, boat ramps, and other gray infrastructures[3]. In areas with dense residential development between 50–90% of shorelines can be armored, whereby, on average, 14% of all U.S. shorelines have been modified from their natural conditions and replaced with artificial structures[3]. This transition represents an extensive loss of natural coastal habitats and the critical ecosystem services they provide.

As more ecologically harmful infrastructure is developed to meet the demands of human population growth, urbanization concurrently alters ecosystem services and functions by negatively impacting biodiversity, ecological conditions and environmental quality, specifically through a decrease in native habitat, increased water pollution, and creation of impervious surfaces[4]. Urbanization may also lead to less resilient and adaptable coastal communities against natural hazards and climate change threats, such as sea level rise and hurricanes. This is because in urban areas, ecosystem functioning is reduced and associated services are lost, resulting in increasing risk of shoreline erosion, saltwater intrusion, storm surges, and coastal flooding[2,5].

These human-environment interactions in coastal ecosystems can lead to, and at the same time be derived by, decisions that will shape the future structure, function, and sustainability of coastal ecosystems[6]. These social decisions (e.g., large-scale policies or individual level choices) can have long-lasting consequences for both the environment and society, especially as coastal development increases. Decisions that modify and change the biophysical nature of the environment (e.g., waterfront residents' decision to use artificial structures for storm protection and shoreline stabilization) impact its ecological functionality[7]. At the same time, these alterations may change the degree of connectivity that individual humans have to their environments, which might extend to broader societies' ecological knowledge[8,9].

Few studies provide evidence that the removal and lack of natural environments in urbanized environments reduces individuals' environmental connectedness and ecological knowledge, and subsequently lowers pro-environmental behaviors[10–12]. This is of critical importance since a general lack of environmental connectedness, and in particular, a lack of ecological knowledge is a phenomenon often used to explain the non-appreciation of, and deleterious behaviors toward, the natural environment, even though many studies theorize these relationships opposed to empirically test them (e.g., see refs. [13,14] and the discussion in ref. [15]

[1]Department of Environmental Health and Engineering, Johns Hopkins University, 3400N Charles Street, Baltimore, MD, USA. [2]Applied Economics Office, National Institute of Standards and Technology, 100 Bureau Drive, Gaithersburg, MD, USA. [3]Department of Community Sustainability, Michigan State University, 480 Wilson Rd, East Lansing, MI, USA. [4]Institute of Marine Sciences, University of California, Santa Cruz, 115 McAllister Way, Santa Cruz, CA, USA. [5]Department of Marine and Environmental Sciences, Northeastern University, 430 Nahant Rd, Nahant, MA, USA. [6]Department of Biology, East Carolina University, 850 NC 345, Wanchese, NC, USA. [7]Coastal Resources Center, University of Rhode Island, 215S Ferry, Narragansett, RI, USA. [8]School of Public Policy and Urban Affairs, Northeastern University, 310 Renaissance Park, Boston, MA, USA.
✉email: pmohamm3@jhu.edu

about “nature-deficit disorder”). Furthermore, if there exists a general lack of ecological knowledge, social decisions at the individual level that reflect these limited perceptions (e.g., utilitarian land-use decisions[12] or waterfront homeowners’ preference to install a bulkhead) can often cascade to larger societal impacts through domino-effects, where individual decisions trigger similar, reactive decisions by neighbors leading to broader societal patterns[16]. For example, Gittman et al.[17] found that one of the stronger predictors of an individual decision to have an armored shoreline was presence of armoring on a neighboring parcel. When considered across a community scale, such societal patterns can alter natural coastal habitats significantly.

In this current study, we investigate the relationship between residents’ knowledge, or mental models, of human-environment interactions, their self-reported pro-environmental behavior, and how these perceptions and behaviors are associated with urbanization. A mental model is the cognitive internal representation of a system in the external world that articulates causal relationships among system components (i.e., abstract concepts)[18,19]. Mental models that represent causal knowledge can be graphically obtained through cognitive mapping techniques in the form of directed graphs, which are networks in which nodes represent concepts (i.e., system components) and graph edges (arrows) represent the causal relationships between the concepts[20]. We combine methods from social science, data science, and network science to conduct an analysis using mental models of coastal residents along an urbanization gradient to better understand the interconnections among urbanization, people's knowledge of human-environment interactions, and their pro-environmental behavior.

We surveyed residents across eight coastal states in the northeast U.S., including Maine, New Hampshire, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, and Delaware. We used a fuzzy cognitive mapping (FCM) approach[21] to elicit mental models of coastal ecosystems with a focus on environmental connectedness, ecosystem health, human wellbeing, climate, and sustainable coasts (see Methods). Here, we propose a concept, Urbanized Knowledge Syndrome (UKS), which represents recurring patterns in urban dwellers’ mental models about natural ecosystems – their internal understanding of how humans and environment interact. Here, syndrome should not be interpreted as a set of medical signs and symptoms which are associated with a particular disease or disorder. These recurring patterns include (1) diminished systems thinking (e.g., complexity of mental models decreases as degree of urban development increases) and (2) the erosion of cognitive diversity (i.e., diversity of mental models among residents decreases as degree of urban development increases). These patterns demonstrate a type of thinking that is simplified to some extent or otherwise limited or focused on fewer social-ecological relationships than exist in reality.

Systems thinking – a holistic view that considers factors and interactions and how they result in a possible outcome – is an important skillset that helps people better understand complex systems and adapt to changes[22]. Individuals with higher degrees of systems thinking are more likely to consider interdependencies, identify leverage points to intervene within the system and produce desired outcomes[23], better anticipate system function and emergence of patterns of behavior[24], and avoid unintended consequences[18]. As such, systems thinking may help coastal residents develop mental models that enable more nuanced reasoning about diverse causal pathways between humans and natural coastal ecosystems[25–28], which may lead to behaviors that are driven by more predominant cognition of complex feedbacks, trade-offs, and reciprocal interdependencies between humans and nature. In contrast, bounded systems thinking (or linear thinking) may lead humans to develop limited cognition of their surrounding world, reduce their ability to accurately and adequately perceive the complexity of the environment they inhabit and interact with[22], and thus may give rise to counter-productive behaviors and decisions[27,29]. For example, a simple causal relationship might be that seawall construction increases coastal protection as a form of structural defense to control shoreline erosion; whereas a more complex relationship might be that seawalls lead to alterations in hydrodynamic processes, which reduces erosion locally and accelerates coastal erosion downstream[30], and at the same time, shoreline armoring can also lead to losses of natural coastal habitats and their critical ecosystem functions[3].

While cities are beneficial to human development, working as engines of socioeconomic change, cultural transformation, and technological innovation, their psychological influences on people and how these influences drive urban residents’ perceptions and behavior must be noted. Firstly, the salience of ecosystem services is limited for inhabitants of more urbanized areas, as compared to rural areas. Exposure to nature provides multiple opportunities for cognitive development which increases the potential for stewardship of the environment and for a stronger recognition of ecosystem functions[13]. Urban residents, however, are more routinely exposed to built environment and gray infrastructure, such as armored shorelines and artificial structures along coastlines, as opposed to natural environment, and thus their local experience of, and connection to, ecosystem services can be limited[31].

Secondly, urbanization generally comes with complex technology and commerce, allowing individuals to meet their needs quickly and through many choices with less appreciation of, and first hand experience with, provisioning ecosystem services (e.g., food comes from many grocery stores not a farm or garden; fish comes over a counter not across a dock or the end of a spear; and potable water comes from a pipeline not a spring or well). This may cause the development of a wider gap in human perceptions of benefits received from natural ecosystems[32], fostering the emergence of societies that are increasingly disconnected and seemingly independent from ecosystem services[31].

Finally, residents of urbanized areas may be exposed to a set of social norms, information, and perspectives that encourage anthropocentric values and thinking including human exemptionalism (“the tendency to see human systems as exempt from the constraints of natural environment”[33]) and human exceptionalism (“the tendency to see humans as biologically unique and discontinuous with the rest of the animal world”[34]), therefore limiting their understanding of the importance and substantiality of reciprocal interdependencies between humans and natural environment[13,34]. These urbanization aspects may spark what we call ‘limits to systems thinking’ in the social-ecological realm.

Therefore, we hypothesize *(H1)* that in more urbanized areas, mental models are predominantly characterized by linear thinking of coastal ecosystems, as opposed to systems thinking, where components are connected mostly by simple causal patterns. This class of mental models is associated with limited cognition of synergies and trade-offs, emergence of global patterns from local relationships, reciprocal interdependencies, and feedback loops between humans and natural ecosystems, which may lead to a gap in residents’ perception of nonlinear complex structures. To test our hypothesis, we analyze the structure of causal relationships using the network structure and graph-theoretic metrics of cognitive maps (i.e., graphical representations of mental models). We use cluster analysis to identify predominant classes of mental models about coastal ecosystems. Distinct clusters of mental models represent archetypal cognitions that individuals develop to perceive human-environment interdependencies[13,27]. We then use network analyses to measure the complexity of causal structures in cognitive maps and determine the overall degree of systems thinking in each cluster (see Methods). Finally, we investigate the association between urbanization and the degree of systems thinking across those clusters.

The second important feature that helps systems adapt to changes is diversity, ranging from ecosystems[35] to economic systems[36]. There is also evidence that these same relationships between diversity and adaptability hold true for cultural knowledge systems, governance systems, and among diverse communities and social institutions that function more effectively as resilient collectives[28,37,38].

In contrast, as cultural homogenization theories explain, survival in cities depends on fitting in and adopting practices that are considered socially normal by the dominant culture[39]. Although cities are magnets for people from all corners of the world with seemingly more diverse composition of race and ethnicity compared to rural areas[40], assimilation of diverse values, beliefs, cultural knowledge, and social norms into a universal, governing culture—sometimes referred to as "cultural colonialism" or "cultural normalization" – is a major component of urban societies[41]. This cultural normalization among urban dwellers is exacerbated by dominant exposure to the universal language and education system, greater access to the Internet, social media and news outlets, and market-driven policies and global standardizations for laws and finance[41].

In addition, an important characteristic of urbanization is the centralization of the population into cities, "where neighborhoods in different regions have similar patterns of roads, residential lots, commercial areas, and aquatic features"[42]. Such physical and environmental homogenization across urban areas, which is visually evident, is influenced by monocentric land-management and policies, economic pressures for land development and use, engineering necessities, codes and standards, and preferences for particular aesthetics and recreations. Prior studies have shown that this homogenization extends to ecological structure, meaning that across urbanized areas, similar built environment and landscape structures can lead to homogenized ecological characteristics, function, and the range of ecosystem services they can supply[42,43].

Here, we argue that homogenization in cultural, physical, and ecological systems also extends to residents' perceptions and understanding of human-environment interactions. We, therefore, hypothesize (*H2*) that increased urbanization is associated with more homogenized mental models of coastal ecosystems. To test our second hypothesis, we measure the structural dissimilarity of individuals' mental models (i.e., cognitive maps) using some of the widely used methods for comparing graphs[44]. We measure the mean of pairwise cognitive distances (i.e., a quantitative metric that represents the mean of graph dissimilarity between any two individual cognitive maps) and compare this metric across clusters of mental models, and thus, explore the correspondence between urbanization and mental model homogenization (i.e., testing the hypothesis that urbanization is associated with more similar mental models in terms of causal structures represented in cognitive maps) (see Methods).

RESULTS

Mental model clusters, demographics, and urbanization

A total of 1397 residents of shoreline counties from eight coastal states in the U.S. participated in the survey study (see Supplementary Fig. 1 for descriptive statistics). Of those, 1226 individuals responded satisfactorily to the questions that intended to collect their FCMs. These responses were then translated to graphical FCMs that represented participants' mental models of coastal ecosystems using networks of nodes and causal links with a focus on human-environment interactions (see Supplementary Fig. 2). We conducted a clustering analysis using the network structural characteristics of these mental models (see Methods). Two clusters of mental models were identified using this approach (Fig. 1a), representing distinct typologies of cognition (i.e., understanding of the human-environment system complexities in a coastal ecosystem). We compared the characteristics of individuals across two clusters in terms of their demographic information, including education, income, home ownership, political affiliation, gender, age, and race. None of those demographic variables were statistically significantly different across the two clusters of mental models, except for age and race (see Supplementary Fig. 3 and Supplementary Table 1 for the results of comparisons). The portion of white race in Cluster-1 was smaller than Cluster-0, while the portions of black/African American race and Asian race in Cluster-1 were larger than Cluster-0, X^2 (6, $N = 1226$) $= 23.804$, $p < .001$. In addition, age in Cluster-1 ($M = 41.84$, $SD = 13.83$) compared to Cluster-0 ($M = 47.49$, $SD = 13.61$) was significantly younger, $t(1224) = 7.211$, $p < 0.001$.

We also compared two other variables across clusters, including the National Center for Health Statistics (NCHS) Urban–Rural Classification (i.e., six-point categorical index for determining the level of urbanization at the county scale),[45] and the percent of armored (hardened) shorelines[7] (see Methods). A chi-square test of independence indicated a significant relationship between mental model clusters and NCHS urbanization levels, X^2 (4, $N = 1226$) $= 26.46$, $p < 0.001$. Post hoc tests revealed that individuals in Cluster-1, as compared to Cluster-0, were more likely to reside in *large central metros* (level 6) and less likely to reside in *small metros* (level 3) (Fig. 1b). Also, the independent-samples *t*-test revealed a statistically significantly higher mean for Cluster-1 than Cluster-0, regarding the percent of armored shorelines, $t(1224) = 3.044$, $p = 0.002$ (Fig. 1c). These findings, collectively, indicated that Cluster-1, as compared to Cluster-0, more strongly represented the social and physical attributes of coastal urban areas. Individuals living in urbanized coastal areas in the U.S. often inhabit large central metros with relatively larger racial diversity,[40] younger population,[46,47] and with greater percentage of natural shorelines being armored and replaced with artificial structures[3].

Urbanization and the limits to systems thinking

To measure how each individual mental model represented (or captured) complex, nonlinear relationships, we used methods for measuring systems thinking using the network structure of the mental models, developed by previous studies[18,25] and applied to multiple contexts[27,28]. Cognitive maps that represent higher levels of systems thinking are expected to have higher prevalence of complex system structures, meaning that they are more likely to explain system trade-offs and synergies (as measured by a graph's Complexity Score), identify emergence of global patterns from local interrelationships (as measured by a graph's Cycles Basis), understand reciprocal (or bidirectional) relationships (as measured by a graph's Reciprocal Micro-Motifs), and capture important feedback loops (as measured by a graph's Feedback Micro-Motifs) (see Methods for more details).

Conversely, we gauged the level of linear thinking by measuring the network hierarchy and structural linearity of cognitive maps using indicators adapted from network-level statistics developed by Krackhardt (1994)[48] (see Methods). For all systems thinking indicators (Fig. 2a), the mean in Cluster-0 was statistically significantly higher than that of Cluster-1. Conversely, for all linear thinking indicators, the relationship was reversed, with these differences in three out of four indicators being statistically significant (Fig. 2b). Given the finding that individuals in Cluster-1 were living in areas with stronger urban characteristics compared to Cluster-0, our results can suggest that urbanization is associated with less systems thinking, and more linear thinking, compared to less urbanized areas.

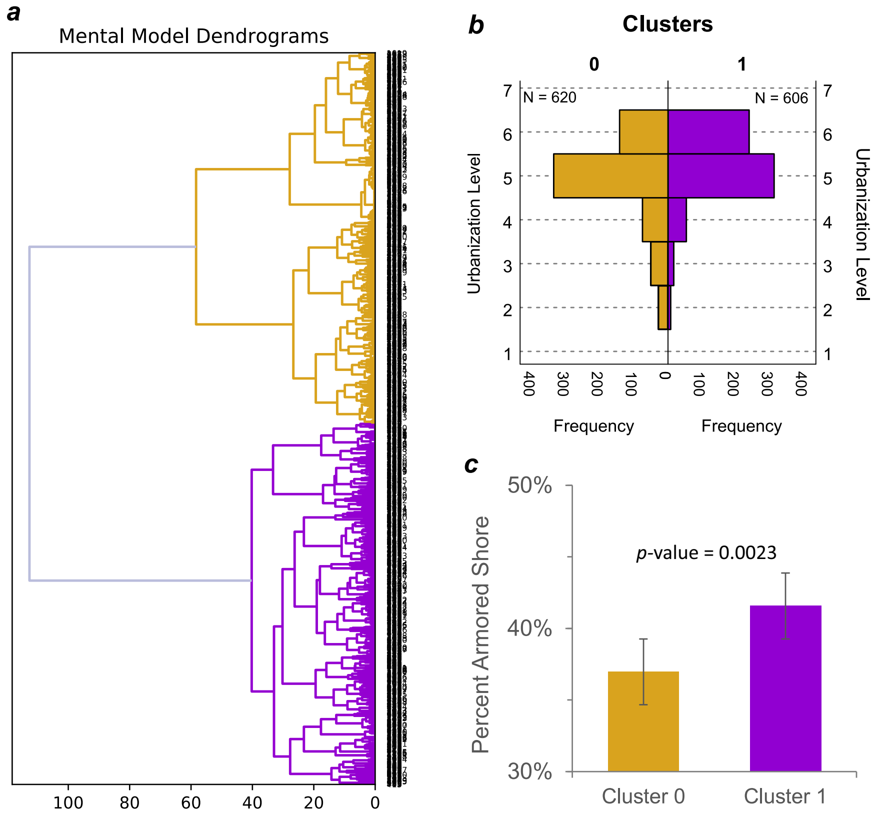

Fig. 1 Clusters of mental models. The dendrograms in (**a**) were cut to achieve two distinct clusters representing different types of mental models based on their network structure. A hierarchical clustering approach using Ward's minimum variance method was conducted on the Euclidean distances between mental models on their general network structural metrics (see Methods). Level of urbanization (**b**) and percent of armored shorelines (**c**) are shown across clusters (error bars denote standard errors).

Urbanization and the erosion of cognitive diversity

To quantify the homogenization of mental models we used a quantitative measure of cognitive distance between individuals based on their mental models' structural characteristics. To compute this distance, we draw on graph and spectral-graph theories to measure graph dissimilarity and assess how individuals' cognitive maps (i.e., mental models) structurally differ from one another (see Methods). The mean of pairwise cognitive distances between mental models within Cluster-1 was statistically significantly smaller than that of Cluster-0 (Fig. 3). This indicated that individuals in Cluster-1 had mental models of coastal ecosystems that were more similar to one another (i.e., homogeneous), compared to mental models in Cluster-0 which showed higher diversity. Importantly, given our findings that Cluster-1 included individuals residing in areas with stronger urban characteristics, Fig. 3 illustrates that urbanization is associated with homogenization of mental models of human-environment interactions.

Additionally, we asked participants to self-report whether they have adopted any of a suite of pro-environmental behaviors (Fig. 4). Here, adoption of each item is a binomial variable (those who consider environmental concerns in their decisions = 1 versus those who do not = 0; this does not group individuals into pro versus anti environmental). Importantly, we detected an increase in odds of adopting pro-environmental behaviors for individuals in Cluster-0 relative to the individuals in Cluster-1 (Fig. 4). Z-tests revealed that for three out of six environmental behavior items, these increases were statistically significant (i.e., the 95% confidence interval did not overlap the null value $OR = 1$). These results suggest that individuals in Cluster-1, those who reside in areas with stronger urbanization attributes, whose mental models also demonstrate stronger evidence of UKS, are less likely to report the adoption of pro-environmental behaviors.

DISCUSSION

Using an example of coastal ecosystems and their underlying social-ecological relationships, our results empirically demonstrate that urbanization and its inherent attributes are positively associated with the homogenization of residents' mental models, and negatively associated with their degree of systems thinking. These findings are very important because homogenized and linear thinking may limit urban coastal residents' ability to perceive complexities of human-environment interactions and consciously choose behaviors that lead to harmony in their relationships with their surrounding natural environments[49]. We claim, though not empirically prove, that (1) a reduction in understanding complexity (i.e., limit to systems thinking) may cause people to oversimplify their impacts on, or connection to, the natural ecosystems leading to environmentally harmful decisions and counterproductive behavior, and (2) a pattern of homogenization in ways of thinking (i.e., erosion of cognitive diversity) may result in increased rigidity in decision making and reduce resilience to social and environmental change in human communities, in similar ways in which increasing rigidity and homogenization reduce economic[36] and ecological systems[35] ability to respond and adapt to changes.

Our findings provide insights into better understanding the dynamics of human-environment interactions. On the one hand, our individual decisions that are shaped, in part, by our mental models[18] may trigger changes to the ecological characteristics of our natural environment. On the other hand, these behaviors may cascade to others through our social connections, which further

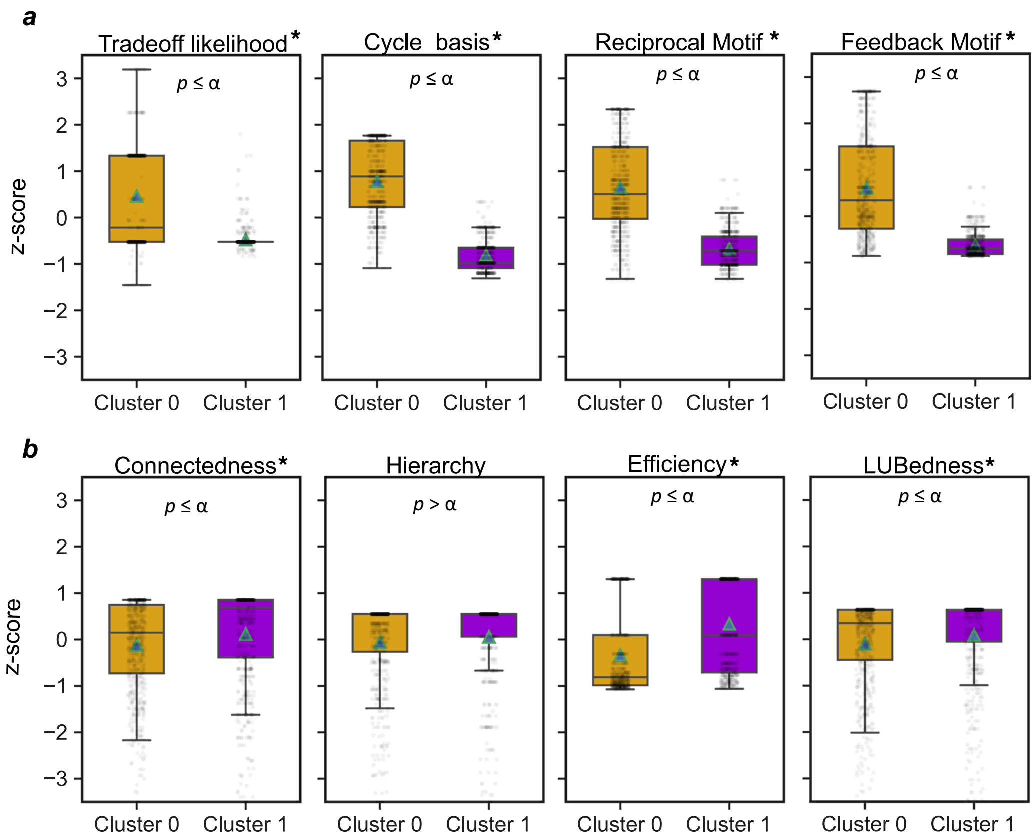

Fig. 2 Comparison of network structural metrics across mental model clusters. Systems thinking (**a**) versus linear thinking (**b**) indicators and their comparison across two distinct clusters of mental models (see Methods for details about each indicator). Independent sample *t*-tests were used with Bonferroni correction for multiple comparisons and an acceptable family-wise error rate (FWER) of 5%. α = Bonferroni adjusted alpha level per test = 0.05/8 = 0.00625. Asterisk denotes *p*-value $\leq \alpha$, which indicates statistical significance. Lower and upper box boundaries denote 25th and 75th percentiles, respectively. Line and triangle inside box denote median and mean, respectively. Vertical extending lines denote adjacent values (i.e., the most extreme values within 1.5 interquartile range of the 25th and 75th percentile of each group).

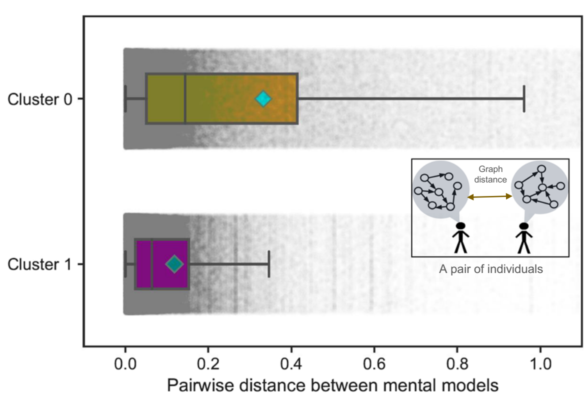

Fig. 3 Pairwise cognitive distances between individual mental models within each cluster. Comparison across clusters was done using an independent sample *t*-test, showing a statistically significant smaller mean for Cluster-1 than Cluster-0 ($p < 0.001$). Lower and upper box boundaries denote 25th and 75th percentiles, respectively. Line and dimond inside box denote median and mean, respectively. Horizontal extending lines denote adjacent values (i.e., the most extreme values within 1.5 interquartile range of the 25th and 75th percentile of each group). The shaded gray dots in the background denote the cognitive distances between all possible pairs of individuals in each cluster.

transform natural ecosystems[16,17,49] and/or feedback to our ecological knowledge, mental models, and decisions through our environmental connections[50,51]. Therefore, the condition of ecological health and the degree to which nature is allowed to function in urban areas can largely be associated with human perceptions, decisions, and practices at the individual or community level through complex feedback dynamics.

People's ecological knowledge and perceptions (i.e., mental models) may vary across individuals depending on their cultural values, life experiences, professions and socioeconomic status, but are also affected by broader hierarchical structures, such as community values, norms and rules, cultural identity, and political and economic institutions[52,53]. In urban settings, institutions typically support rules and norms that have a need for general application and foster socioeconomic and political stability (land-use planning, urban design, environmental management, and development policies)[54]. A recent study has provided empirical evidence that modification of the natural environment driven by such monocentric land-management practices and human dominance has led urban areas across the U.S. to represent similar built environment characteristics and ecological homogenization, despite the fact that they differ in their regional climate and biophysical characteristics[42].

We expanded upon these previous findings and further tested the hypothesis that human dominance of urban ecosystems and

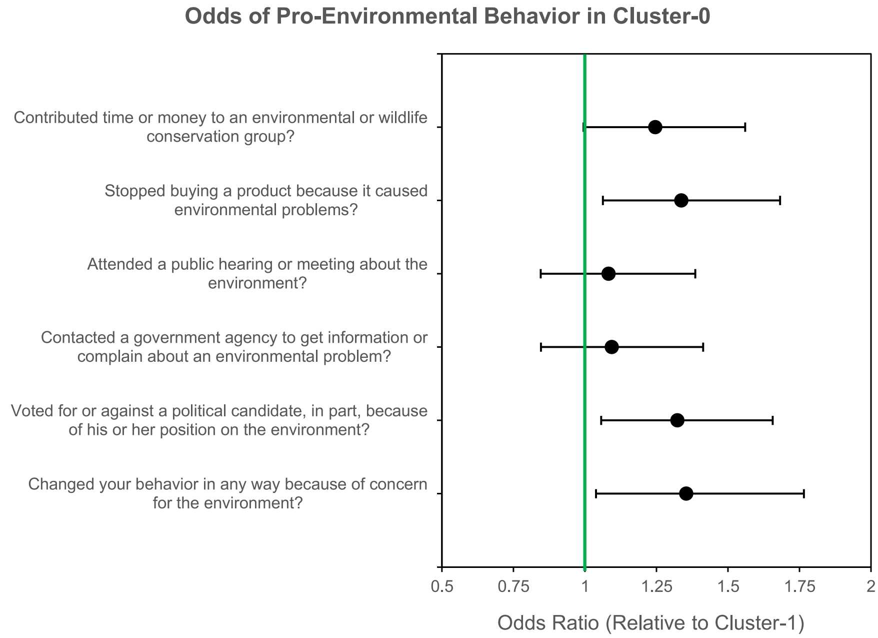

Fig. 4 Odds ratio and 95% confidence intervals (i.e., error bars) for pro-environmental behavior in Cluster-0 relative to Cluster-1. Pro-environmental behavior items whose 95% confidence intervals do not cross the null value (OR = 1) indicate statistically significantly different odds across two clusters with p-value ≤ 0.05.

their ecological homogenization extends to urban residents' mental models of human-environment interactions within coastal ecosystems. Importantly, this mental model homogenization can encourage, or be encouraged by, environmental behavior and knowledge in urban settings that embrace more homogeneity, convention and norms, thereby potentially eroding already-weakened human-nature connections and stewardship[55,56].

One of the limitations of the current study is that it does not determine the direction of causality, nor does it intend to make causal inferences about the relationship between preference for environmental attributes, ecological knowledge, and structure of mental models. Yet, our results importantly suggest that a reinforcing-feedback loop among these factors exists, as having less experience and connectedness with the natural world can result in ecological knowledge erosion that may then influence behaviors and preferences that further degrade the environment and impact ecosystems. However, it remains unclear which one comes first. It is, therefore, possible that homogenized mental models and the erosion of ecological knowledge —what we refer to as UKS—results in further degradation of coastal ecosystem services through a self-reinforcing trap[56]. This may contribute to less resilient and adaptable ecosystems to future social-ecological challenges. Also, we were more interested in capturing large-scale phenomena independent of how and whether respondents perceived to be living in an urban-to-rural gradient (and independent of distance from green spaces or other amenities).

Projections suggest that by 2050, nearly 70% of the human population will become urban dwellers[57]; therefore, beyond identifying and diagnosing UKS, future work needs to focus more on better treating it. Here, we identify three overarching, but not mutually exclusive, treatments: (1) designing local institutions with heterogeneous land-management policies in a decentralized setting where local level decisions and governance systems nested into higher level governance settings; (2) fostering environmental connectedness through building cultural, architectural and cognitive links between humans and the natural environment; and (3) promoting adaptive learning and ecological knowledge that accommodates biodiversity and enhances the resilience of social-ecological coastal ecosystems[42]. These potential treatments are further explained below.

Firstly, moving away from centralized management towards a more polycentric and nested system may favor sustainable management of coastal urban areas[58,59]. Institutional diversity, while nested into higher level governance settings, can theoretically enable a multi-level governance system that balances out the dominance of highly centralized institutional arrangements and therefore encourages enhanced institutional fit[60]. Additionally, having greater diversity among environmental leadership could lead to more innovative solutions with implications for addressing racial and environmental justice issues[61]. It may better preserve urban policy and decision heterogeneity at the local level (i.e., multiple local institutions, each of which operates with some degree of autonomy for decision making), while operationalizing under governance settings with unified overarching goals, norms and rules[62]. Polycentricity, thereby, may engage citizens with more diverse institutional settings and decisions that can potentially enable them to break the self-reinforcing UKS trap.

Secondly, It is of importance to recognize dominant values and representations that lead to UKS and to identify how they can evolve towards more satisfying environmental sustainability in tandem with social and cultural flourishing in urbanized settings[63]. Leveraging humans' natural affinity towards nature (i.e., "Biophilia")[64] and increasing urban vegetation can benefit people's physical and mental health. In addition, encouraging the connection between humans and nature supports cognitive function and helps to enhance systems thinking. In urban locations, increased nature, green space, and nature-based approaches can be considered a necessity, opposed to an amenity. However, in more diverse urban areas, resources are not distributed equally across society. Instead, the distribution of such space often disproportionately benefits predominantly white and higher-income communities[65]. Communities of color, in contrast, are disproportionately impacted by environmental issues and have historically been (and currently are) far more likely to live in areas with less access to nature and less socioeconomic investment in nature-based approaches (e.g., see refs. [65,66]). To apply an equity and environmental justice lens to addressing UKS, green space and nature-based solutions within urban settings would ideally be highly connected, of high ecological quality, and widely accessible across socioeconomic sectors.

Finally, using programs like citizen science to enhance the ability of individuals in urban settings to engage with nature may contribute effectively to treating UKS[67]. These programs help residents identify and respond to local environmental issues by way of fostering adaptive learning about human-environment interactions through evidence-based practices. In addition, Kransy and Tidball (2012)[13] presented a call to all institutions active in cities, including governments, non-profits, the private sector and universities to promote enhanced urban stewardship through Civic Ecology; a process by which local environmental stewardship actions can be initiated to enhance both the green infrastructure and community wellbeing of urban and other human-dominated systems.

While urbanization continues, as a result of the confluence of several interacting factors, it will likely lead to more homogenized social, economic, and indeed environmental systems. Hence, recognizing and addressing UKS requires a multi-faceted approach focused on establishing appreciation for, and understanding of, important human-environmental relationships that maintain ecological quality and human wellbeing in balance.

METHODS

Survey design

To test our hypotheses, we report survey panel data representing more than 1350 coastal residents. A primary section of the survey was designed to elicit individual mental models through the use of fuzzy cognitive mapping (FCM) method. Mental models that represent causal knowledge (e.g., how social and ecological components are interconnected in a coastal urban ecosystem) can be graphically obtained through cognitive mapping techniques in the form of directed graphs, which are networks in which nodes represent concepts (i.e., system components) and graph edges (arrows) represent the causal relationships between the concepts. Additionally, causal connections are assigned a negative or positive numerical weight with an absolute value in the interval of zero and one, corresponding to the magnitude and sign of the relationships. Our survey instrument involved a series of questions designed to (step-1) select FCM concepts, and (step-2) define causal relationships between the concepts and assign edge weights. The first step provided participants with the following prompt:

- *In the next few questions, we would like for you to describe your view of healthy and sustainable coastal shorelines. To start, please select all of the components that you believe are important for coastal shorelines. You may also enter one category that you believe is important but not included in the list.*

The list of concepts was: Marine life, Water Quality, Marshes & Natural Habitats, Recreational & Cultural Activities, Beaches, Seawalls & Engineered Shorelines, Protection from Storms, Water Access (boat ramps & piers), and Commercial Fisheries & Livelihoods.

Next, to assign edge weights, we asked a series of pairwise questions for all selected concepts, with an example being: How would you describe the influence of Seawalls & Engineered Shorelines on Recreational & Cultural Activities? (See Supplementary Fig. 2). In addition to mental models, this paper also reports on survey questions on environmentalism and demographics. The full survey instrument is provided at the project's Open Science Foundation (OSF) page.

Survey data collection

This study was conducted with approval of Northeastern University's Institutional Review Board (IRB), and written informed consent was acquired from all participants. We used Qualtrics Research Panels to recruit a sample of ~1400 individuals in coastal counties from Delaware to Maine. Qualtrics panel samples are proportioned to the general public and randomized before deployed. To evaluate and assure data quality, we applied a multi-step process during and after survey implementation. First, we included two attention check questions to detect "straight-lining" (i.e., respondents who repeatedly selected the same answer). Next, we set a completion time threshold of 50% of the mean completion time to identify 'speeders' (i.e., respondents who rapidly answer questions without closely reading them)[68]. Finally, after the survey closed, we reviewed all survey responses to flag data quality issues. Following this review, all bad responses were replaced by Qualtrics and new responses were subsequently reviewed. In addition, we excluded from mental model analyses those respondents whose FCMs' number of connections (i.e., edges) were at the 10th percentile, which resulted in excluding FCMs with equal or fewer than five edges.

After data collection, we appended county-level data on urbanization and shoreline condition to the survey data. An urbanization gradient was used to explore potential associations between residents' mental models and degree of urbanization. We used National Center for Health Statistics (NCHS) Urban–Rural Classification Scheme for Counties. This urbanization gradient consisted of six categories: two Nonmetropolitan categories and four Metropolitan categories including small metro, medium metro, large fringe metro, and large central metro. This urbanization gradient was created from a series of factors but most closely associated with county population density (see ref. [38] for more details). We also used Gittman et al. (2015)'s county-level estimates of NOAA's Environmental Sensitivity Index (ESI) for the percent of armored (hardened) shorelines (see ref. [7] for more details).

Mental model clustering

To analyze the mental model data, we drew on network analysis to measure structural metrics of FCMs that provide important information about how a person's mental model represents interdependencies. The general network structural metrics we used to cluster mental models included total number of concepts (i.e., nodes in a graph), number of connections (i.e., nonzero links between nodes), sum of the absolute value of the edge weights, centrality of each concept (i.e., sum of the absolute value of edge weights, for those edges entering or exiting that concept), network density (i.e., number of nonzero edges proportion to the number of all possible edges), the number of drivers (i.e., nodes with no edges entering them), the number of receivers (i.e., nodes with no edges exiting them), the ratio of receivers to drivers, and the number of ordinary concepts (i.e., nodes that are neither drivers nor receivers). For more details see Ozesmi & Ozesmi (2004; Table 1)[69]. These structural metrics of FCMs have been widely used by prior studies to highlight differences in people's mental models (e.g., see refs. [69–72]). We performed a hierarchical clustering approach using Ward's minimum variance method on the Euclidean distances between mental models. Using this clustering approach, we firstly converted each mental model to its vector of general structural metrics and secondly searched for clusters of mental models such that the variance of sum of squares between their vectors of structural metrics was minimized[73].

Systems thinking versus linear thinking

We used four "Systems Thinking" indicators to measure the extent to which the structural relationships among system components indicate complex versus simple causal thinking: Firstly (1), we calculated Complexity score which measures the ratio of receiver nodes to the driver nodes. This score can be a proxy for the potential occurrence (or the likelihood) of causal structures that represent trade-offs (or synergies) where one action affects multiple valued outcomes. Secondly (2), we found the Cycles Basis of a mental model which is a minimal collection of fundamental cycles in its underlying graph (i.e., undirected version of the digraph) such that any cycle in this underlying graph can be written as a sum of cycles in the basis[74]. The size of this collection is a positive number which can indicate the extent to which a mental model considers local relationships that give rise to global patterns—a complex system's property called "emergence"[24]. Thirdly (3), we calculated the frequency of Reciprocal Motifs that are unique collections of two nodes (i.e., dyads), that are linked through bidirectional causal relationships, and thus represent the cognition of reciprocal relationships in a mental model. Finally (4), we calculated the frequency of Feedback Motifs, that are unique collections of three nodes (i.e., triads), that form a closed feedback loop, either clockwise or counterclockwise. The higher the number of Feedback Motifs, the higher the cognition of complex relationships that represent fundamental causal feedback loops[18].

Conversely, to gauge the level of linear thinking in cognitive maps, we began by measuring indicators that are adapted from network dimensions developed by Krackhardt (1994)[48] to describe the amount of hierarchy in networks. Firstly (1), we used network Connectedness concept which represents the probability that every pair of distinct nodes is joined by a path. This condition can be approximated by measuring the fraction of dyads (pairs of nodes) that are adjacent in a network, relative to the maximum possible adjacent dyads (i.e., the higher the density of connections, the higher the probability that every pair of distinct nodes is joined by a path). Secondly (2), we used network Hierarchy concept which represents the probability that a dyad with a connecting path in one direction do not have a connecting path in the other direction. This can be approximated by quantifying the fraction of dyads that are adjacent in only one direction (i.e., they do not have bidirectional adjacency), relative to the maximum possible adjacent dyads. Thirdly (3), we used the network Efficiency concept which represents the probability that each component of the underlying graph has exactly *n*-1 edges where *n* is the number of nodes in that component. This can be approximated by reversing the network inefficiency, which is the difference between actual number of edges minus one and the maximum possible number of edges. And finally (4), we used the least-upper boundedness (*LUBedness*) concept which captures the probability that a dyad share an antecedent node, and if they share multiple antecedents, whether those antecedents have a single shared antecedent[18,48]. This can be approximated by counting the number of dyads that have a common antecedent relative to the maximum number of possible dyads that could potentially meet this criterion.

Independent sample *t*-tests were used to compare both systems thinking and linear thinking indicators of cognitive maps across two clusters of mental models.

Cognitive distances and mental model homogenization

To measure mental model homogenization, we perform network comparisons by defining a measure of distance between FCM graphs. Each FCM is a directed, weighted graph *G*(*V*,*E*), with *V* being the set of nodes (i.e., concepts) and *E* being the set of edges (i.e., causal connections). We compute the distance between a pair of FCMs by taking into account two measures:

$$d_J = 1 - J\left(A_1^d, A_2^d\right) \quad (1)$$

Where A_1^d andA_2^d, are the unweighted adjacency matrices.

(1) The Jaccard Distance between unweighted adjacency matrix (A^d) of two FCMs. For each graph *G*, A^d is a $n \times n$ square matrix, where *n* is the number of nodes, and the elements of the matrix $[a_{ij}]$ indicate whether pairs of nodes *i* and *j* are adjacent ($[a_{ij}] = 1$) or not ($[a_{ij}] = 0$) in the graph. In FCMs, the presence and absence of the connections is a binomial variable, representing the extent to which one individual includes or excludes the directed causal relationship between two concepts when representing a complex system. The Jaccard coefficient *J* for two graphs is defined as $\left(A_1^d, A_2^d\right) = \frac{A_1^d \cap A_2^d}{A_1^d \cup A_2^d}$, and their Jaccard distance is calculated as follows:

(2) The Euclidian Squared Distance between underlying graphs' spectra of two FCMs. For each graph *G*, the spectrum is the set of eigenvalues of its normalized Laplacian[75,76] that contains useful information about the principal properties and structure of a graph, which has important implications for graph comparisons[76–78]. In addition, one prior study[38] demonstrated that the Euclidian squared distance between the spectra of two FCMs perfectly matches the differences in how individuals perceived the system dynamics. Importantly, all eigenvalues of the normalized Laplacian are real and non-negative[76], thereby offering a practical tool for measuring graph distances. Given two graphs $G_1(V_1,E_1)$ and $G_2(V_2,E_2)$ we find a set of all eigenvalues for each normalized Laplacian as their spectra. Similar to the approach outlined in refs. [79,80], we compute the Euclidian squared distance between the graphs' spectra as follows:

$$d_s = \sum_{i=1}^{k^*} (\lambda_{1i} - \lambda_{2i})^2 \quad (2)$$

Where d_s is the Euclidian squared distance between underlying graphs' spectra of two FCMs, λ_i is the *i*th largest eigenvalue and $\lambda_i \geq 0 \; for \; \forall i$. We find the smallest *k* such that the sum of the *k* largest eigenvalues constitutes at least 90% of the sum of all of the eigenvalues. If the values of *k* are different between the two graphs, we use the smaller one (k^*).

These two measures of distance between pairs of FCMs are complementary. Thus, to jointly acknowledge the weight and directionality of causal connections in FCMs, we define the cognitive distance between two FCMs as follows:

$$CD = d_s \times d_J \times \varphi \quad (3)$$

Were φ is the standardization coefficient for mapping *CD* to a normalized range between [0,1]. All individual FCMs were converted into adjacency matrices (see Supplementary Fig. 2) and the cognitive distances between any pairs of maps were computed using Eq. 3. For each cluster of cognitive maps, we measured the cognitive distance between all pairs of individuals within that cluster, that is, the dissimilarity of their mental models. Independent sample *t*-tests were used to compare the means of cognitive distances across two clusters.

DATA AVAILABILITY

All data supporting the findings of this study including data for obtaining the FCM of individuals are available and can be downloaded as data spreadsheets from OSF at https://osf.io/4c3en/?view_only=84e1e6bb36634d9ca209aad6f95f7255.

CODE AVAILABILITY

Codes for replicating figure and mental model analyses are publicly available and can be obtained from https://osf.io/4c3en/?view_only=84e1e6bb36634d9ca209aad6f95f7255.

Received: 20 October 2021; Accepted: 24 March 2022;
Published online: 04 May 2022

REFERENCES

1. Small, C. & Nicholls, R. J. A global analysis of human settlement in coastal zones. *J. Coast. Res.* **19**, 584–599 (2003).
2. Neumann, B., Vafeidis, A. T., Zimmermann, J. & Nicholls, R. J. Future coastal population growth and exposure to sea-level rise and coastal flooding-a global assessment. *PloS One* **10**, e0118571 (2015).
3. Scyphers, S. B. et al. Designing effective incentives for living shorelines as a habitat conservation strategy along residential coasts. *Conserv. Lett.* **13**, e12744 (2020).
4. Wu, J. Urban ecology and sustainability: The state-of-the-science and future directions. *Landsc. Urban Plan.* **125**, 209–221 (2014).
5. (US), C. C. S. P. Climate change impacts in the United States, highlights: US national climate assessment. (US Global Change Research Program, 2014).
6. Scyphers, S. B. & Lerman, S. B. Residential landscapes, environmental sustainability and climate change. in *From sustainable to resilient cities: global concerns and urban efforts* (Emerald Group Publishing Limited, 2014).
7. Gittman, R. K. et al. Engineering away our natural defenses: an analysis of shoreline hardening in the US. *Front. Ecol. Environ.* **13**, 301–307 (2015).
8. Jordan, A. & Russel, D. Embedding the concept of ecosystem services? The utilisation of ecological knowledge in different policy venues. *Environ. Plan. C Gov. Policy* **32**, 192–207 (2014).
9. Hicks, C. C. & Cinner, J. E. Social, institutional, and knowledge mechanisms mediate diverse ecosystem service benefits from coral reefs. *Proc. Natl. Acad. Sci.* **111**, 17791–17796 (2014).
10. Pereira, M. & Forster, P. The relationship between connectedness to nature, environmental values, and pro-environmental behaviours. *Reinvention: An Int. J. Undergrad. Res.* **8** (2015). http://www.warwick.ac.uk/reinventionjournal/archive/volume8issue2/pereira.
11. Alcock, I., White, M. P., Pahl, S., Duarte-Davidson, R. & Fleming, L. E. Associations between pro-environmental behaviour and neighbourhood nature, nature visit frequency and nature appreciation: Evidence from a nationally representative survey in England. *Environ. Int.* **136**, 105441 (2020).
12. McDaniel, J. & Alley, K. D. Connecting local environmental knowledge and land use practices: a human ecosystem approach to urbanization in West Georgia. *Urban Ecosyst.* **8**, 23–38 (2005).
13. Tidball, K. G. & Krasny, M. E. Urban environmental education from a social-ecological perspective: Conceptual framework for civic ecology education. *Cities Environ.* **3**, 11 (2010).
14. Beery, T. H. & Wolf-Watz, D. Nature to place: Rethinking the environmental connectedness perspective. *J. Environ. Psychol.* **40**, 198–205 (2014).
15. Fletcher, R. Connection with nature is an oxymoron: A political ecology of "nature-deficit disorder. *J. Environ. Educ.* **48**, 226–233 (2017).
16. Scyphers, S. B., Picou, J. S. & Powers, S. P. Participatory conservation of coastal habitats: the importance of understanding homeowner decision making to mitigate cascading shoreline degradation. *Conserv. Lett.* **8**, 41–49 (2015).

17. Gittman, R. K. et al. Reversing a tyranny of cascading shoreline-protection decisions driving coastal habitat loss. *Conserv. Sci. Pract*. **3**, e490 (2021).
18. Levy, M. A., Lubell, M. N. & McRoberts, N. The structure of mental models of sustainable agriculture. *Nat. Sustain* **1**, 413–420 (2018).
19. Jones, N. A., Ross, H., Lynam, T., Perez, P. & Leitch, A. Mental models: an interdisciplinary synthesis of theory and methods. *Ecol Society* **16** (2011). https://doi.org/10.5751/ES-03802-160146.
20. Gray, S. A., Zanre, E. & Gray, S. R. J. Fuzzy cognitive maps as representations of mental models and group beliefs. in *Fuzzy Cognitive Maps for Applied Sciences and Engineering*. 29–48 (Springer, 2014).
21. Kosko, B. Fuzzy cognitive maps. *Int. J. Man. Mach. Stud.* **24**, 65–75 (1986).
22. Senge, P. M. & Sterman, J. D. Systems thinking and organizational learning: Acting locally and thinking globally in the organization of the future. *Eur. J. Oper. Res.* **59**, 137–150 (1992).
23. Meadows, D. H. *Thinking in systems: A primer*. (chelsea green publishing, 2008).
24. Schlüter, M. et al. Capturing emergent phenomena in social-ecological systems. *Ecol. Soc*. **24** (2019). https://doi.org/10.5751/ES-11012-240311.
25. Gray, S. Measuring systems thinking. *Nat. Sustain* **1**, 388–389 (2018).
26. Hamilton, M., Salerno, J. & Fischer, A. P. Cognition of complexity and trade-offs in a wildfire-prone social-ecological system. *Environ. Res. Lett.* **14**, 125017 (2019).
27. Lalani, B. et al. Mapping farmer perceptions, Conservation Agriculture practices and on-farm measurements: The role of systems thinking in the process of adoption. *Agric. Syst.* **191**, 103171 (2021).
28. Aminpour, P. et al. The diversity bonus in pooling local knowledge about complex problems. *Proc. Natl. Acad. Sci.* **118**, 5 (2021).
29. Duguma, L. A., Minang, P. A. & van Noordwijk, M. Climate change mitigation and adaptation in the land use sector: from complementarity to synergy. *Environ. Manage.* **54**, 420–432 (2014).
30. Balaji, R., Sathish Kumar, S. & Misra, A. Understanding the effects of seawall construction using a combination of analytical modelling and remote sensing techniques: Case study of Fansa, Gujarat, India. *Int. J. Ocean Clim. Syst.* **8**, 153–160 (2017).
31. Gómez-Baggethun, E. et al. Urban ecosystem services. in *Urbanization, biodiversity and ecosystem services: Challenges and opportunities* 175–251 (Springer, Dordrecht, 2013).
32. Young, R. F. Interdisciplinary foundations of urban ecology. *Urban Ecosyst* **12**, 311–331 (2009).
33. Williams, J. Thinking as natural: another look at human exemptionalism. *Hum. Ecol. Rev.* **14**, 130–139 (2007).
34. Arenson, M. & Coley, J. D. Anthropocentric by default? Attribution of familiar and novel properties to living things. *Cogn. Sci.* **42**, 253–285 (2018).
35. Oliver, T. H. et al. Biodiversity and resilience of ecosystem functions. *Trends Ecol. Evol.* **30**, 673–684 (2015).
36. Duchek, S., Raetze, S. & Scheuch, I. The role of diversity in organizational resilience: a theoretical framework. *Bus. Res* **13**, 387–423 (2020).
37. Page, S. E. A complexity perspective on institutional design. *Polit. Philos. Econ* **11**, 5–25 (2012).
38. Aminpour, P. et al. Wisdom of stakeholder crowds in complex social-ecological systems. *Nat. Sustain* **3**, 191–199 (2020).
39. Appadurai, A. Disjuncture and difference in the global cultural economy. *Theory. Cult. Soc* **7**, 295–310 (1990).
40. Cromartie, J. *Rural America at a glance 2018 edition*. (2018).
41. Amsler, S. Cultural colonialism. *Blackwell Encycl. Sociol*. 1–3 (2007).
42. Groffman, P. M. et al. Ecological homogenization of urban USA. *Front. Ecol. Environ.* **12**, 74–81 (2014).
43. Groffman, P. M. et al. Ecological homogenization of residential macrosystems. *Nat. Ecol. Evol.* **1**, 1–3 (2017).
44. Tantardini, M., Ieva, F., Tajoli, L. & Piccardi, C. Comparing methods for comparing networks. *Sci. Rep.* **9**, 1–19 (2019).
45. Ingram, D. D. & Franco, S. J. *2013 NCHS urban-rural classification scheme for counties*. (US Department of Health and Human Services, Centers for Disease Control and~…, 2014).
46. Pew Research Center, May 2018, "What Unites and Divides Urban, Suburban and Rural Communities". https://www.pewresearch.org/social-trends/2018/05/22/what-unites-and-divides-urban-suburban-and-ruralcommunities/.
47. Bureau, U. S. C. New census data show differences between urban and rural populations. *Brief No. CB16-210* (2016).
48. Krackhardt, D. Graph theoretical dimensions of informal organizations. *Comput. Organ. Theory* **89**, 123–140 (1994).
49. Bürger, J. & Laguna-Tapia, A. Individual homogenization in large-scale systems: on the politics of computer and social architectures. *Palgrave Commun* **6**, 1–9 (2020).
50. Schwermer, H. et al. Modeling and understanding social-ecological knowledge diversity. *Conserv. Sci. Pract.* **3**, e396 (2021).
51. Aminpour, P., Schwermer, H. & Gray, S. Do social identity and cognitive diversity correlate in environmental stakeholders? A novel approach to measuring cognitive distance within and between groups. *Plos One* **16**, e0244907 (2021).
52. Bang, M., Medin, D. L. & Atran, S. Cultural mosaics and mental models of nature. *Proc. Natl. Acad. Sci.* **104**, 13868–13874 (2007).
53. Rosenbaum, E. Mental models and institutional inertia. *J. Institutional Econ*. 1–18 (2021). https://doi.org/10.1017/S174413742100059X.
54. Chapin III, F. S., Kofinas, G. P., Folke, C. & Chapin, M. C. *Principles of ecosystem stewardship: resilience-based natural resource management in a changing world*. (Springer Science & Business Media, 2009).
55. Liu, J. et al. Complexity of coupled human and natural systems. *Science.* **317**, 1513–1516 (2007).
56. Boonstra, W. J. & de Boer, F. W. The historical dynamics of social-ecological traps. *Ambio* **43**, 260–274 (2014).
57. Un, D. Revision of world urbanization prospects. *New York: United Nations Department of Economic and Social Affairs* (2018).
58. Brondizio, E. S., Ostrom, E. & Young, O. R. Connectivity and the governance of multilevel social-ecological systems: the role of social capital. *Annu. Rev. Environ. Resour.* **34**, 253–278 (2009).
59. Ostrom, E. *Governing the commons: The evolution of institutions for collective action*. (Cambridge university press, 1990).
60. Epstein, G. et al. Institutional fit and the sustainability of social-ecological systems. *Curr. Opin. Environ. Sustain.* **14**, 34–40 (2015).
61. Garlington, S. B. & Collins, M. E. Addressing environmental justice: Virtue ethics, social work, and social welfare. *Int. J. Soc. Welf.* **30**, 353–363 (2021).
62. Carlisle, K. & Gruby, R. L. Polycentric systems of governance: A theoretical model for the commons. *Policy Stud. J.* **47**, 927–952 (2019).
63. House, E., O'Connor, C., Wolf, K. L., Israel, J. & Reynolds, T. Outside our doors: The benefits of cities where people and nature thrive. *The Nature Conservancy: Seattle, WA, USA* (2016).
64. Wilson, E. O. *Biophilia*. (Harvard university press, 1984).
65. Wolch, J. R., Byrne, J. & Newell, J. P. Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough. *Landsc. Urban Plan.* **125**, 234–244 (2014).
66. Sister, C., Wolch, J. & Wilson, J. Got green? Addressing environmental justice in park provision. *GeoJournal* **75**, 229–248 (2010).
67. Jordan, R. et al. Studying citizen science through adaptive management and learning feedbacks as mechanisms for improving conservation. *Conserv. Biol.* **30**, 487–495 (2016).
68. Zhang, C. & Conrad, F. Speeding in web surveys: The tendency to answer very fast and its association with straightlining. *Surv. Res. Methods* **8**, 127–135 (2014).
69. Özesmi, U. & Özesmi, S. L. Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach. *Ecol. Modell.* **176**, 43–64 (2004).
70. Furman, K. L., Aminpour, P., Gray, S. A. & Scyphers, S. B. Mental models for assessing coastal social-ecological systems following disasters. *Mar. Policy.* **125**, 104334 (2021).
71. Gray, S., Chan, A., Clark, D. & Jordan, R. Modeling the integration of stakeholder knowledge in social-ecological decision-making: benefits and limitations to knowledge diversity. *Ecol. Modell.* **229**, 88–96 (2012).
72. Stier, A. C. et al. Integrating expert perceptions into food web conservation and management. *Conserv. Lett.* **10**, 67–76 (2017).
73. Murtagh, F. & Legendre, P. Ward's hierarchical agglomerative clustering method: which algorithms implement Ward's criterion? *J. Classif.* **31**, 274–295 (2014).
74. Paton, K. An algorithm for finding a fundamental set of cycles of a graph. *Commun. ACM.* **12**, 514–518 (1969).
75. Cohen-Steiner, D., Kong, W., Sohler, C. & Valiant, G. Approximating the spectrum of a graph. In *Proceedings of the 24th acm sigkdd international conference on knowledge discovery & data mining* 1263–1271 (2018).
76. Chung, F. R. K. & Graham, F. C. *Spectral graph theory*. (American Mathematical Soc., 1997).
77. Bollobás, B. *Modern graph theory*. vol. 184 (Springer Science & Business Media, 2013).
78. Newman, M. *Networks: An Introduction*. (OUP Oxford, 2010).
79. Koutra, D., Parikh, A., Ramdas, A. & Xiang, J. Algorithms for graph similarity and subgraph matching. (2011). https://www.cs.cmu.edu/~jingx/docs/DBreport.pdf. Retrieved (01-10-2021).
80. Gera, R. et al. Identifying network structure similarity using spectral graph theory. *Appl. Netw. Sci* **3**, 2 (2018).

ACKNOWLEDGEMENTS

This work was funded by the Northeast Sea Grant Consortium and National Science Foundation (OCE-1215825) to J.H.G. and S.B.S. and the National Science Foundation's Graduate Research Fellowship Program to K.L.F.

AUTHOR CONTRIBUTIONS

P.A., S.A.G., S.B.S conceptualized the work. P.A., S.A.G., S.B.S, J.H., I.T., and K.L.F. wrote the original draft. S.B.S., J.H.G., M.R., L.J., and R.K.G. led data collection. P.A. designed and implemented code and analyzed data. M.W.B., J.H.G., and M.R. provided theoretical background and verification. Acquisition of the financial support for the project leading to this publication was led by S.B.S., J.H.G., M.W.B., R.K.G., and M.R. All authors contributed to manuscript review & editing and approved the manuscript prior to submission.

COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s42949-022-00054-0.

Correspondence and requests for materials should be addressed to Payam Aminpour.

Reprints and permission information is available at http://www.nature.com/reprints

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.