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Cognition of feedback loops in a fire-prone social-ecological system

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A R T I C L E I N F O

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A B S T R A C T

Increasing wildfire severity highlights the need for large-scale shifts in management of fire-prone landscapes. While prior research has focused on cognitive biases, social norms, and institutional disincentives that limit reform, such factors are best understood as components of feedback loops that operate within complex adaptive systems. We evaluated the prominence and function of feedback loops embedded in cognitive maps—beliefs about patterns of causal relationships that drive system dynamics—elicited from a diverse cross-section of stakeholders in a fire-prone region in the U.S. West. We demonstrate that cognition of feedback loops is rare among individuals, but increasingly prominent within aggregations of cognitive maps, which underscores the importance of collaborative decision-making. Our analysis further reveals a bias toward perception of amplifying feedback loops and of loops in which management actions result in desirable outcomes, which points to areas where progress may be made in reforming wildfire risk governance.

1. Introduction

Large-scale and uncontrollable "megafires" have become increasingly common globally, driven in part by changing climatic conditions along with the accumulation of fuels as a result of longstanding fire-suppression policies (Ager et al., 2014; Flannigan et al., 2013; Hessburg et al., 2005; Millar and Stephenson, 2015; Stephens et al., 2014). In the United States, the years 2015–2018 were the costliest wildfire years in history, with suppression alone exceeding $2 billion for the first time in 2015 and $3 billion in 2018 (NIFC, 2021). The question of how to mitigate wildfire risk in ways that protect human safety, local economies, forest health, and a range of other values has no easy answer. In wildfire-prone social-ecological systems, land managers and other decision-makers must grapple with considerable uncertainty resulting from complex interactions of ecological, physical, political, and economic processes that contribute to wildfire risk (Fischer et al., 2016a; Prior and Eriksen, 2013; Spies et al., 2014; Steelman, 2016).

This paper examines the challenge of reducing vulnerability to wildfire through computational analysis of how stakeholders individually and collectively perceive a defining feature of complex systems: feedback loops. Addressing environmental management challenges requires disentangling the sets of nested or otherwise interdependent feedback loops that can contribute to non-linear dynamics that may prompt regime shifts or may compel systems to persist in undesirable states (Coop et al., 2020; Fischer et al., 2016a). Cognition of feedback loops reveals a capacity for systems thinking, which can facilitate problem solving in complex decision-making settings (Levy et al., 2018; White, 2008, 1997). In evaluating stakeholder perceptions of feedback loops, we ask (i) how cognition of feedback loops varies at individual and collective levels, (ii) whether perceived feedback loops amplify or self-regulate system processes, and (iii) whether perceived feedback loops are desirable or undesirable, based on the outcomes of management interventions.

We situate our research at the intersection of complex systems and cognitive sciences, and we make distinct contributions to both fields. We approach complexity in social-ecological systems through a framework that understands resilience as an emergent property of individual cognition and group-level decision-making within larger systems processes (Schill et al., 2019; Schlüter et al., 2019). In the tradition of research on alternative stable states in ecosystems and social-ecological systems, we regard resilience as a measure of a system's tendency to persist in a particular state despite external shocks and stressors, rather than shift to an alternative state (Lewontin, 1969; Holling, 1973; Scheffer et al., 2001; Folke, 2006). Just as ecological processes may

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contribute to or diminish resilience, so may human cognitive, social, and institutional processes. Stakeholders embedded in social-ecological systems have agency, and their beliefs shape their individual and collective behaviors, which in turn affect system dynamics (Beratan, 2007; Klöckner, 2013). In settings characterized by strong and extensive coupling between human and natural processes, stakeholder cognition of system dynamics shapes individual and collective actions to sustain, interrupt, or otherwise manage those processes, which may facilitate a system's persistence in one state or its conversion to another. We specifically focus on stakeholders' perceptions of the numerous feedback loops that structure complex systems (Levin et al., 2013; Martin and Schlüter, 2015), and we open a new vein of research on the relationships between resilience and complexity by evaluating how cognition of feedback loops depends on the level of aggregation of belief structures. Finally, we address the need for greater understanding of how collaborative models of governance that bring together diverse sets of knowledge grapple with complex natural resource management challenges (Newig and Fritsch, 2009; Rodela et al., 2012).

1.1. Feedback loops in complex social-ecological systems

Feedback loops refer to coupled dynamics between pairs of factors, which are often mediated by intervening effects of other factors. Feedbacks are a defining feature of hazard-prone social-ecological systems and may result from the interplay between human and biophysical drivers at multiple levels of spatial and social organization (Fischer, 2018; Liu et al., 2007; McAllister et al., 2006). The potential for feedback loops to generate non-linear dynamics constitutes another form of complexity that challenges the capacity of individuals to predict outcomes of risk mitigation actions.

Dominant research on feedback loops in wildfire-prone and other social-ecological systems has primarily focused on analysis of a single or

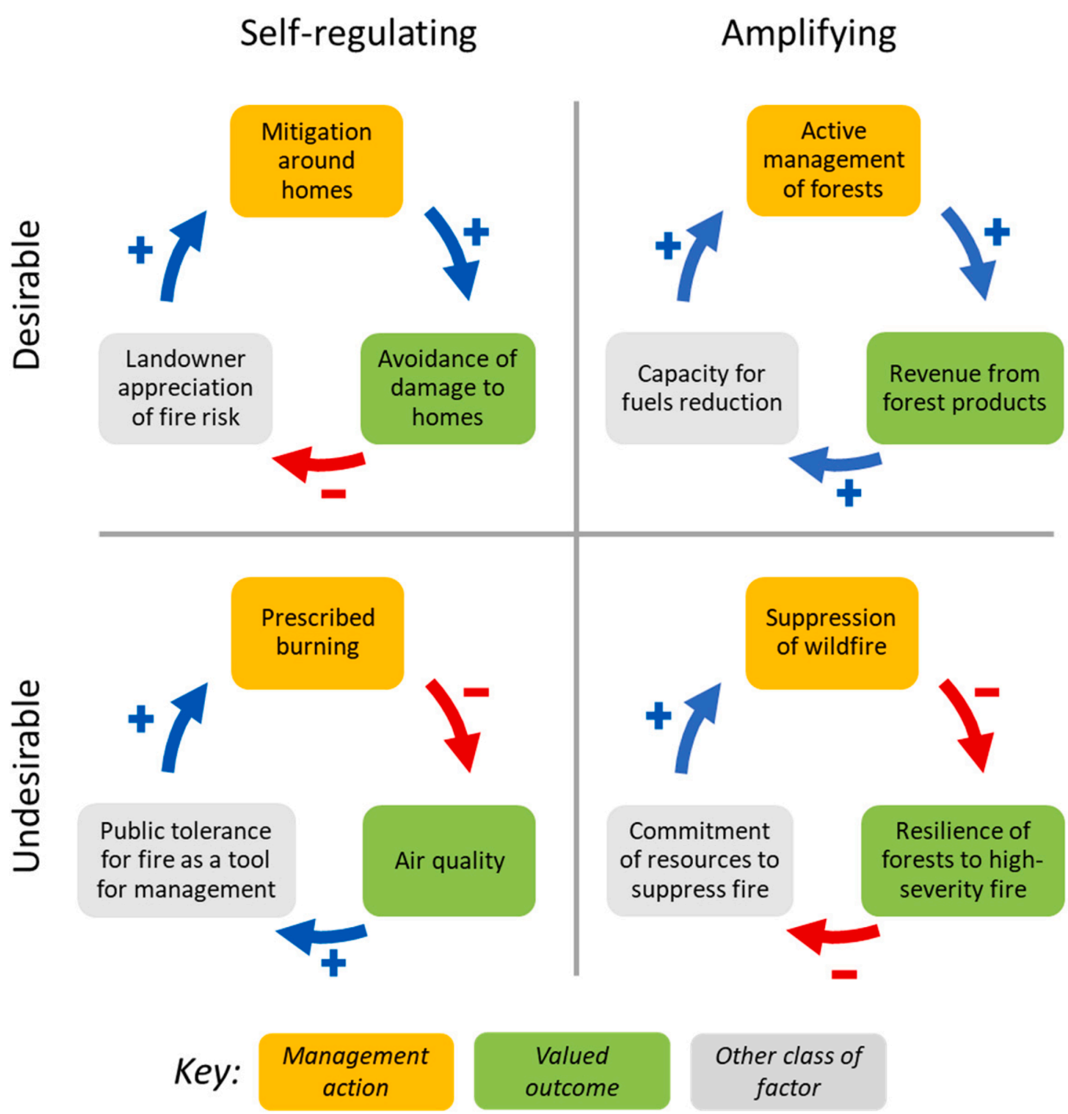

Fig. 1. A classification of perceived feedback loops. The classification distinguishes between whether feedbacks are amplifying or self-regulating and whether management actions result in desirable or undesirable outcomes. An outcome is desirable when an increase in an action enhances a value (e.g., air quality). Feedback loops are comprised of factors that represent quantitative variables. Although these factors may represent a range of different types of factors, each feedback loop depicted in the figure features a management action (yellow) and a focal outcome on a value (green). Other classes of factors are depicted in gray. Feedback loops depicted in the figure are among those present in the dataset analyzed. For simplicity, the figure only includes feedback loops with three factors but feedback loops could feature more or fewer factors in practice. Likewise, feedback loops depicted in the figure feature direct causal linkages from actions to outcomes, but such linkages could be mediated by one or more other factors. Arrow color indicates whether the causal effect is positive (blue) or negative (red). For example, the upper-left feedback loop is self-regulating because it involves an odd number of negative effects (i.e., the single relationship indicating that avoidance of damages from wildfire reduces appreciation of fire risk) and is desirable because the action (mitigation around homes) results in a beneficial outcome (avoided damages).

small number of feedback loops conceived to drive system outcomes, and are commonly identified prior to analysis (e.g., Calkin et al., 2015; Chin et al., 2016). For example, ample research highlights how decades of fire suppression in western forests has allowed fuels to build up, steadily increasing the likelihood of high-severity fires, and in turn motivating the need for greater and greater investments in fire suppression over time. However, there is limited understanding of factors that shape all but the most prominent feedback loops operating in social-ecological systems. This gap is important because such feedback loops are typically both composed of and interdependent with other feedback loops.

Evaluation of large numbers of feedback loops at multiple scales in turn enables analysis of their characteristics and their effects on systems outcomes. Feedbacks may be amplifying or self-regulating (Fig. 1). Amplifying feedback loops result from coupled dynamics among a set of variables in which a change in any variable will be reinforced by corresponding changes in the other variables (Meadows and Wright, 2008). Feedbacks may also be characterized as desirable or undesirable, based on the degree to which valued outcomes (e.g., air quality, protection of homes) are enhanced through management actions (e.g., prescribed fire, understory thinning). Distinguishing between value-free (e.g., amplifying versus self-regulating) and value-explicit (e.g., desirable versus undesirable) dynamics can help characterize system-level outcomes (Higuera et al., 2019).

1.2. Cognition of feedback loops

In complex environmental decision-making settings, an appreciation of feedback loops can help individuals and groups identify leverage points and other opportunities for achieving management goals (Biggs et al., 2015; Preiser et al., 2018). However, research suggests that cognition of feedback loops is rare relative to appreciation of other types of relationships among causal factors, such as the perception that factors are each affected by multiple other factors (Levy et al., 2018). Evidence that individuals have difficulty perceiving feedback loops underscores the challenge of environmental problem solving, namely the likelihood that decision-makers fail to account for the ways in which actions exacerbate path dependency (Barreteau et al., 2020; Kotir et al., 2017).

Yet, there has been limited research on how individuals collectively perceive feedback loops, which likewise has important implications for decision-making. Collaborative environmental decision-making processes may enable diverse groups of stakeholders to exchange information about distinct values, beliefs, and knowledge of dynamics that shape complex social-ecological systems (Beratan, 2007; Halbrendt et al., 2014). The degree to which such exchanges facilitate systems thinking—including cognition of feedback loops—remains an open question. Compounding this uncertainty, there is limited research on the nature of feedback loops that stakeholders perceive to structure social-ecological systems. In particular, an understanding of how stakeholders distinguish between amplifying and self-regulating, as well as desirable and undesirable, feedback loops can reveal barriers and opportunities for management to address complex environmental problems (Biggs et al., 2015).

1.3. Network analysis of perceived feedback loops

Perceived feedback loops can be conceptualized as network configurations in cognitive maps. Cognitive maps are representations of the factors, as well as the relationships among them, that structure an individual's understanding of a complex system (Fig. 2). In most social-ecological systems, including fire-prone landscapes, factors may encompass demographic trends, governance processes, human behavior, policies, biophysical characteristics, and environmental trends. In research that aims to understand how people conceptualize the dynamics in social-ecological systems, cognitive maps are often used to elicit descriptive information about the structure of linkages among factors (e.g., Özesmi and Özesmi, 2004; Vanwindekens et al., 2013; but see Levy et al., 2018). Some cognitive mapping approaches elicit information about the magnitude of effects (e.g., a 1-unit increase in factor X causes a 1.5-unit decrease in factor Y) (e.g., Gray et al., 2015). Other approaches only collect information about the sign of the effect (i.e., positive or negative), or note only the direction of causality (e.g., Levy et al., 2018), and still others simply record that a relationship exists (e.g., Hoffman et al., 2014).

Because cognitive maps are fundamentally relational datasets, network science offers an appropriate set of tools for their analysis. One analytical approach involves the use of network-level indices to characterize cognitive maps, for example on the basis of their overall levels of connectivity, hierarchy, or centralization (Özesmi and Ozesmi, 2003; Gray et al., 2012; Vasslides and Jensen, 2016). Another approach examines the prevalence of network substructures (also known as network motifs; Milo et al., 2002) that represent theoretically important patterns of relationships among a limited number of causal factors. For example, in their study of cognitive maps of thought leaders in sustainable agriculture, Levy et al. (2018) examine six substructures, each of which involves relationships among two or three causal factors and represents

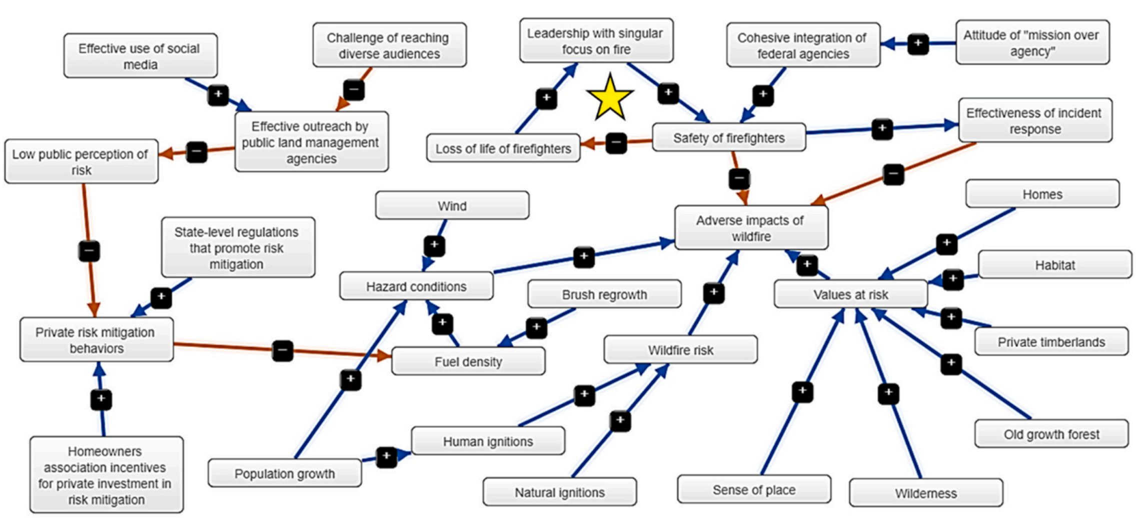

Fig. 2. An example of a cognitive map featuring perceived causal relationships among factors related to wildfire risk. Blue arrows represent positive relationships, while negative relationships are depicted as orange arrows. The three factors surrounding the yellow star comprise a feedback loop. This cognitive map is based on one respondent's map and was edited for legibility (the number of factors was reduced).

a different dimension of systems thinking. In our case, the network concept of "cycles" captures the concept of feedback loops and provides a means of measuring these features of the system. In network terminology, a 2-cycle relationship is a reciprocal feedback loop (i.e., A directly affects B and B directly affects A). A 3-cycle relationship depicts a triad (i.e., A directly affects B, B directly affects C, and C directly affects A). In this way, it is possible to measure feedback loops that feature an arbitrary number of mediating effects (i.e., n-cycles) in any cognitive map.

1.4. Research questions

We evaluate three research questions. Our first question examines how the prominence of feedback loops varies as a function of the integration of knowledge sets from increasing numbers of cognitive maps. As we describe in more detail below, we created "social cognitive maps" by aggregating individual cognitive maps (Özesmi and Özesmi, 2004; Gray et al., 2012, 2014; Singh and Chudasama, 2017; Hamilton et al., 2019b; Aminpour et al., 2021). While such aggregate cognitive maps are not equivalent to cognitive maps elicited directly from groups of interacting stakeholders, recent research highlights their potential to reveal collective intelligence of complex relationships among social-ecological processes (Aminpour et al., 2020). Stakeholders make environmental decisions individually and collectively, and this research question examines how one key indicator of systems thinking—cognition of feedback loops—varies as a function of the aggregation of knowledge sets. In particular, recent research suggests that multi-stakeholder decision-making processes can elicit knowledge that spans multiple domains of expertise by effectively merging cognitive maps of participating stakeholders (Galafassi et al., 2017). Whether such settings enable forms of systems thinking—including cognition of feedback loops (Meadows and Wright, 2008; White, 1997)—is an open question. We evaluated this proposition by measuring the prominence of feedback loops in individual cognitive maps, as well as in aggregate cognitive maps constructed from random samples of two, four, six, and eight individual maps. This approach, described in greater detail in section 2.4, enabled us to measure how the potential for systems thinking—as indicated by cognition of feedback loops—varies as a function of the size of stakeholder groups. This question is important because it evaluates the potential for communication among stakeholders to facilitate systems thinking within groups, thereby enabling decisions that better grapple with social-ecological complexity.

Our second question examines how the likelihood that perceived feedback loops are amplifying or self-regulating varies as a function of the characteristics of their constituent causal factors. As we describe in greater detail in section 2.5, we focused on factors classified as environmental trends and shocks, as well as different management approaches. We expected these classes of factors to be particularly important predictors of whether feedback loops were amplifying versus self-regulating because they related directly to the ecological processes and human interventions that shape system dynamics. Alternative stable state theory suggests that self-regulating feedback loops function to hold systems in a particular basin of attraction characterized by a set of conditions, and that the system may transition to a different set of conditions (i.e., a different state, with its own basin of attraction) when these self-regulating feedback loops are suppressed, eliminated, or overwhelmed (Bowman et al., 2015; Scheffer et al., 2001). Indeed, research suggests that systems that resist regime shifts do so because of the synchronous effects of multiple self-regulating feedback loops (Hastings and Gross, 2012). Because researchers commonly consider single feedback loops, which are considered a priori to be amplifying or self-regulating, there has been little research on factors associated with amplifying versus self-regulating feedback loops, as perceived by stakeholders. Addressing this gap is important because successful policy interventions hinge upon stakeholders' understandings of how management actions create, maintain, or interrupt different types of feedback loops (Biggs et al., 2015). Accordingly, this question sheds light on how people perceive feedback loops as amplifying or self-regulating, which in turn improves understanding of how people conceptualize complex dynamics, including the relative merits of different environmental management strategies.

Our third question examines how the likelihood that perceived feedback loops are desirable varies as a function of the characteristics of their constituent causal factors, again focusing on factors related to environmental trends and shocks, as well as management approaches. While dominant research on feedback loops in social-ecological systems evaluates desirability from the standpoint of the entire system—whether the system exists in a basin of attraction that enhances or restricts ecosystem health or human wellbeing (e.g., Hruska et al., 2017)—our approach sheds light on factors that affect the persistence of the numerous individual feedback loops that aggregate to shape such macro-level outcomes. In particular, desirable feedback loops may represent incentive structures, which may not necessarily produce desirable outcomes at the system-level. This question directs attention to the implications of making management decisions based on intermediate outcomes (e.g., air quality, profitability), which may be at odds with broader goals, such as progress towards fire-adapted communities and landscapes.

2. Materials and methods

2.1. Study system

We study cognition of feedback loops that shape wildfire risk in the Eastern Cascades Ecoregion (ECE) in Oregon, USA, which has been studied extensively as a model system for research on fire-prone social-ecological systems (e.g., Spies et al., 2014; Fischer et al., 2016b; Hamilton et al., 2019a). The ECE extends over approximately 3.3 million ha, and ranges between 500 and 3260 m in elevation. Dominant tree species include ponderosa pine (*Pinus ponderosa*), lodgepole pine (*Pinus contorta*), western juniper (*Juniperus occidentalis*), mountain hemlock (*Tsuga mertensiana*), Douglas-fir (*Pseudotsuga menziesii*), grand fir (*Abies grandis*), and white fir (*Abies concolor*). Wildfire is a natural ecological process in the ECE. Historically, regions at lower elevations were characterized by frequent and low severity fires while high severity fires were characteristic in moister forests at higher elevations (Agee, 1993; Merschel et al., 2014). Current wildfire regimes bear the influence of human management activities. Beginning in the 19th century, wildfire exclusion and suppression, to protect homes and timber value, along with the harvest of large trees, contributed to the accumulation of dense flammable vegetation that currently provides the conditions for wildfires that can overwhelm containment and spread over large areas (Merschel et al., 2014; Steen-Adams et al., 2017; Stephens et al., 2014). In the ECE, diverse groups of stakeholders conduct a range of forest and fire management activities, including understory thinning, prescribed burning, and the creation of fuel breaks (Charnley et al., 2017; Olsen et al., 2017). The region is a patchwork of public, private, and tribal lands, which are managed by federal and state agencies, corporations, individuals, and tribal governmental organizations alongside numerous policy and advocacy organizations that do not manage land themselves but seek to influence decisions about land management. This diversity of stakeholder groups results in numerous perspectives on the causes and consequences of wildfires, as well as distinct preferences for addressing wildfire risk (Fischer et al., 2016b; Hamilton and Salerno, 2020).

2.2. Participant recruitment and data collection

We collected cognitive maps from 111 individuals involved in efforts to address wildfire risk in the ECE. These individuals were selected from a study population identified as part of a 2011–2013 study on wildfire risk in the same study region (Fischer et al., 2016b; Spies et al., 2014). Specifically, the population (n = 787) was the network of individuals who were nominated as collaborative partners, sources of information, and/or influential stakeholders by research participants in the earlier study. Because a core goal of our research was to understand how diverse stakeholders conceptualize wildfire risk, we stratified the population by geographic subregion and by primary affiliation (e.g., federal agency, non-governmental organization, private forest owner), and randomly selected individuals across both strata. We recruited participants by phone and email. Data were collected during in-person meetings, typically in participants' places of work or in public locations. All activities were approved by the University of Michigan Institutional Review Board (ID: HUM00133263). An active literature compares cognitive maps of different stakeholder groups in environmental management/governance settings, often with particular attention to the distinction between experts and non-experts, such as practitioners or resource users (Aminpour et al., 2020; Soler et al., 2012; Zaksek and Árvai, 2004). Each of our participants had extensive cultural and institutional knowledge about government agencies and other organizations, deep familiarity with social, economic, and political processes within the region, rich place-based ecological knowledge, and/or extensive experience implementing forest and fire management practices. These different sets of knowledge are all relevant to an understanding of the fire-prone social-ecological system. Consequently, we regard all participants in our study as experts, even though many do not have the formal credentials (e.g., professional degrees) that commonly serve to designate domain expertise.

Cognitive map data were collected using MentalModeler software (Gray et al., 2013). We prompted participants to identify factors that they perceived to affect and be affected by wildfire risk, directly and indirectly, as well as the relationships by which they considered factors to be linked. Because we requested that participants identify quantitative variables (e.g., "wildfire severity" rather than "wildfire"), relationships corresponded to causal linkages, and we additionally prompted participants to indicate whether each link represented a positive or negative effect.

We coded the set of factors from all 111 cognitive maps using parent, child, and subchild classes (see Supplemental Materials for more details), which enabled us to identify which factors corresponded to wildfire risk management actions and to different types of valued outcomes. We classified factors as management actions if they represented fire response, forest management, legal, or outreach/education strategies. Factors were classified as valued outcomes if they referred to effects on desirable features or qualities (additional classes are presented in Supplemental Materials). During this process, we also identified sets of factors that appeared in multiple cognitive maps and referred to the same phenomena (e.g., "prescribed fire" and "prescribed burning"), which were given a common name. Along with factors that were identified using the same name by participants themselves, these common factors were used to link and subsequently aggregate cognitive maps, as described in section 2.4.

2.3. Measurement of perceived feedback loops

Our unit of analysis was instances of perceived feedback loops, which we operationalized as directed cycles (i.e., circuits of nodes). Specifically, we used the "simple cycles" algorithm in the Python language package NetworkX (Hagberg et al., 2008) to identify all closed paths in each cognitive map network. While most cycles contained a small number of factors, this approach allowed us to measure cycles of any size. We coded cycles as "amplifying" or "self-regulating" based on whether the product of all causal linkages between nodes that comprise the cycle was positive or negative (e.g., given A (+) B (-) C (-) A, 1*-1*-1 = 1, a cumulatively positive effect, hence an amplifying feedback loop). We coded each cycle as "desirable" or "undesirable" based on whether the "action" node had a cumulatively positive or negative effect on the "valued outcome" node within the cycle.

2.4. Analysis of how perception of feedback loops varied at different levels of social cognition

To evaluate how the prominence of feedback loops varied at different levels of social cognition, we aggregated different numbers of cognitive maps, ranging from 1 (i.e., individual cognitive maps) to 6. The relatively low maximum level of aggregation reflects our interest in comparing feedback loop cognition among individuals with feedback loop cognition among aggregations of even just several individual cognitive maps. Aggregate maps resulted from the union of individual maps' sets of nodes (causal factors) and linkages. Through this process, individual maps were joined on the basis of nodes that were common to each one (Fig. 3). Following Özesmi and Özesmi (2004) and subsequent work (Aminpour et al., 2021; Gray et al., 2012, 2014; Hamilton et al., 2019b; Singh and Chudasama, 2017), we regarded the resulting aggregate maps as "social cognitive maps" because they represented the integration of knowledge sets from two or more individuals' cognitive maps.

For each level of social cognition n (except for $n = 1$), we drew 200 random samples of n individual cognitive maps and aggregated them. This process generated 711 cognitive map networks (200 maps of $n = 2$, 4, and 6, plus 111 maps of $n = 1$). As the union of their constituent cognitive maps, aggregate maps necessarily have the same or greater numbers of substructures, including feedback loops. For example, the mean number of feedback loops in individual cognitive maps was 3.7, which rose to 7.9 in aggregate maps of level $n = 2$. Consequently, rather than directly compare counts of feedback loops, we used a modeling approach that controlled for basic structural characteristics of cognitive maps, which varied considerably within and between levels of aggregation.

We measured the degree to which feedback loops were under- or overrepresented in cognitive maps constructed from varying numbers of individual cognitive maps by comparing empirical counts of feedback loops with the distributions of feedback loops from simulated cognitive maps that captured fundamental structural characteristics of the empirical cognitive map. This strategy enabled us to measure the relative prominence of feedback loops in each map, based on the expected number of feedback loops in randomly generated networks with the same basic structural characteristics as the empirical network. Our approach drew upon and extended recently-developed methods for evaluating the prevalence of substructures in cognitive map networks (Levy et al., 2018; Aminpour et al., 2021), which are part of a broader set of approaches that use baseline models to generate a reference distribution as a basis for determining the degree to which particular network characteristics are significantly under- or overrepresented (Mayhew, 1984; Anderson et al., 1999; Jasny, 2012; Stivala and Lomi, 2021).

To each of the individual and aggregate cognitive maps, we fit an exponential random graph model (ERGM) using the statnet package (Handcock et al., 2008) in the R statistical environment (R Core Team, 2018). Each ERGM included the "edges" and "isolates" terms to estimate the likelihood for linkages between pairs of factors and to control for the fact that all factors in all cognitive maps were linked to at least one other factor. This approach is similar to the approach used by Levy et al. (2018) and Aminpour et al. (2021), who used uniform random graphs to control for the number of factors and linkages in cognitive maps in order to evaluate the relative prominence of substructures involving two or three factors. Our approach differs only slightly, in that we used ERGMs to additionally constrain random graphs to have no isolated factors, as was the case in all empirical networks, and we did not fix the number of linkages. In the statnet syntax, each ERGM was specified as ergm (<network> ~ edges + isolates). Subsequently, using the coefficients of each ERGM, we simulated 1000 cognitive map networks, which each had the same set of factors, no isolated factors, and approximately the same number of linkages as the empirical cognitive map network modeled in the ERGM. For each of the resulting 1000 networks as well as the empirical network, we then calculated the number of feedback loops

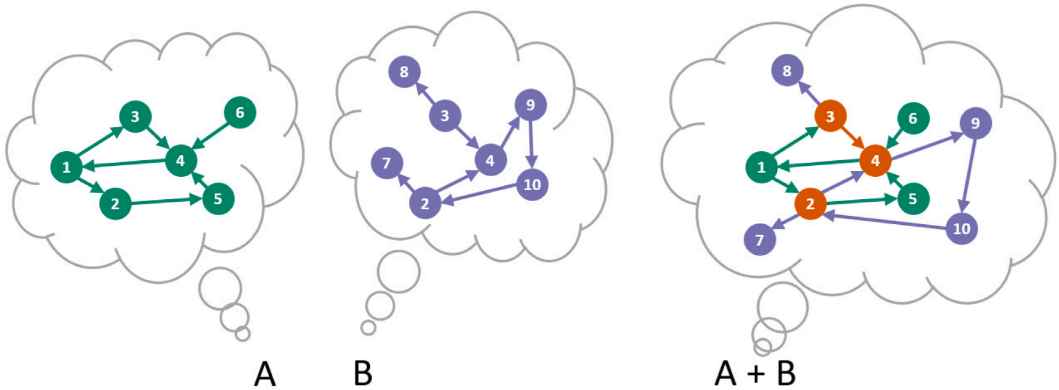

Fig. 3. Aggregation of cognitive maps. Cognitive maps of individuals were aggregated by taking the union of causal factors and linkages in their networks. For example, the union of cognitive maps of individuals A (with 6 factors and 7 linkages) and B (7 factors, 7 linkages) results in an aggregate cognitive map with 10 factors and 13 linkages, with common factors and the single common linkage depicted in brown. Aggregate cognitive maps may feature structural characteristics absent in individual maps. For example, the aggregate map of individuals A and B contains feedback loops present in A's map (e.g., 1 → 3 → 4) and B's map (e.g., 2 → 4 → 9 → 10), as well as feedback loops that are not present in either map (e.g., 1 → 2 → 4 and 2 → 5 → 4 → 9 → 10).

using the "cycle" ERGM term (summary(<network> ~ cycle(2:< network size>)). Importantly, this approach allowed us to measure feedback loops of varying size, ranging from two factors (i.e., a reciprocal linkage) to the theoretical maximum size that corresponded to the number of factors in the cognitive map network. To evaluate the degree to which feedback loops were under- or overrepresented, relative to expectations, we calculated z-scores based on the counts of feedback loops in empirical cognitive maps and the distributions of counts from simulated maps.

2.5. Statistical models of feedback loop perception

We fitted Bayesian multilevel binomial regression models to evaluate factors associated with the valence (i.e., amplifying rather than self-regulating) and desirability of feedback loops. Bayesian methods provided computational efficiency in estimating complex statistical models using large datasets and allowed us to estimate precise measures of uncertainty on group-level parameters relative to likelihood-only methods (Gelman et al., 2013; McElreath, 2015). Our research questions were operationalized into statements of the likelihood of observing a particular type of perceived feedback loop as a function of the additive contribution of multiple characteristics of feedback loops. We term each of these observations *instances*. This representation is fundamentally about the odds of observing one of two types of feedback loops, which dictated the use of a binomial logistic model (see Supplementary Information for additional details, including formal model specification).

Our dependent variables measured whether feedback loops are amplifying rather than self-regulating and whether they are desirable rather than undesirable. Independent variables measured the number of factors of particular classes present in each feedback loop. We focused on classes related to environmental change and forest/fire management actions. Specifically, the variable "environmental trends" measured the number of factors within each feedback loop that were classified as an indicator of mid- to long-term change in ecosystems (e.g., "dense bitterbrush"), while the variable "environmental shocks" measured the number of factors classified as short-term events (e.g., "fire in wilderness areas"). Likewise, management actions encompassed the variables "fire response" (tactics for fire management, e.g., "aggressive initial response to fire"), "legal actions" (approaches for using the judicial system, e.g., "litigation"), "forest management" (strategies for modifying vegetation to address forest quality and/or fire risk reduction, e.g., "create fuel breaks"), and "outreach and education" (approaches for information exchange, e.g., "fire district facilitating neighbor-neighbor interaction").

3. Results

The prominence of perceived feedback loops increases with the number individual cognitive maps aggregated (Fig. 4). We find that individuals (aggregation = 1) perceive fewer feedback loops than should be expected based on structural characteristics of their cognitive map networks. As increasing numbers of cognitive maps are aggregated, the prominence of feedback loops likewise increases. Even when just two cognitive maps are aggregated, the mean number of feedback loops is greater than should be expected from the basic structural characteristics

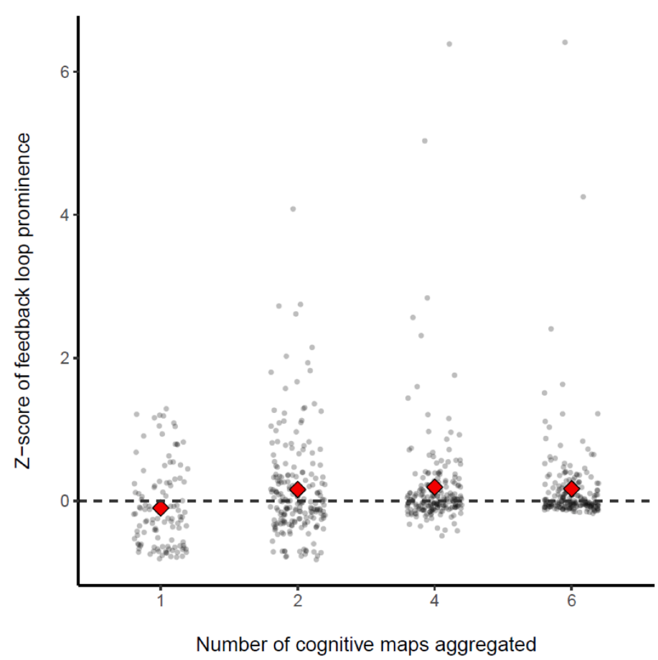

Fig. 4. The prominence of feedback loops as increasing numbers of cognitive maps are aggregated. Grey points represent cognitive maps. At levels of aggregation > 1, individual cognitive maps were randomly sampled and aggregated. Conditioning on basic structural characteristics of each cognitive map (e.g., number of factors, number of relationships among factors), we simulated 1000 cognitive maps and measured the prominence of feedback loops using z-scores based on the counts of feedback loops in empirical cognitive maps and the distributions of counts from simulated maps. Red diamonds indicate the mean prominence of feedback loops at each level of cognitive map aggregation (i.e., 1 = individual cognitive maps, 2 = aggregation of two cognitive maps).

of those aggregate cognitive map networks.

Perceived feedback loops are more likely to be amplifying rather than self-regulating (Fig. 5A), based on the results of a Bayesian multilevel binomial regression model. The model also estimates the likelihood that perceived feedback loops are amplifying (versus self-regulating) as a function of the types of factors that comprise them. We focused on factors related to environmental dynamics and management approaches. While environmental trends are more likely to be featured in amplifying feedback loops in cognitive maps, self-regulating feedback loops are more likely to feature environmental shocks. All management approaches tend to be associated with self-regulating feedback loops in stakeholders' cognitive maps.

Perceived feedback loops tend to be desirable (Fig. 5B), based on a separate Bayesian multilevel binomial regression model. The model further indicates that amplifying feedback loops tend to be particularly desirable. To disentangle this latter finding from the results of the model presented in Fig. 5A, we interacted each variable with a dummy variable indicating whether each perceived feedback loop was amplifying. Amplifying feedback loops featuring environmental trends are more likely to be desirable, while amplifying feedback loops that include environmental shocks tend to be undesirable. Management approaches generally contribute to undesirable feedback loops in cognitive maps and this tendency is especially pronounced among management approaches embedded in amplifying feedback loops.

Finally, in Fig. 6, we observe how factors featured in feedback loops vary based on the two dimensions that characterize our conceptual framework depicted in Fig. 1 (amplifying/self-regulating as well as desirable/undesirable). Very few factors are prominently featured in undesirable feedback loops (i.e., are located in the lower quadrants) and these few factors in turn do not appear in many feedback loops. With the exception of some factors in the upper-right region of the plot, the factors that appear in the most feedback loops are located near the origin (with a tendency to be featured in self-regulating and desirable feedback loops). This means that factors embedded in high numbers of feedback loops also tend to be embedded in sets of feedback loops that are balanced in terms of being amplifying vs self-regulating and desirable vs undesirable.

4. Discussion and conclusion

Addressing wicked environmental management challenges in hazard-prone systems requires a more holistic understanding of the complex relationships between social and ecological drivers of environmental risk. This study posits that environmental outcomes are the emergent product of multitudes of small-scale interactions, among which feedback loops—"the basic operating unit of a system" (Meadows and Wright, 2008, p. 5)—are especially consequential. Management decisions undertaken by individuals and groups alike reflect belief structures (Freeman et al., 2020), which highlights the importance of understanding how environmental stakeholders perceive feedback loops.

Our results show that feedback loops are underrepresented in the cognitive maps of individuals. This finding bolsters conclusions drawn from prior research that individuals have difficulty engaging in complex systems thinking (e.g., Levy et al., 2018; White, 2008), and is particularly noteworthy given that our respondents were among the most knowledgeable stakeholders engaged in wildfire management in the study region. However, we also find that feedback loops are more prominent in aggregate cognitive maps, thereby providing evidence for the possibility that small groups (including even pairs of individuals) may more readily conceptualize feedback loops than individuals. In social-ecological systems in which environmental management policies may be contested by stakeholders with different values, collaborative decision-making processes are often championed as a means for diffusing conflict and providing a pathway for consensus and compromise (Abrams, 2019). Our research suggests that such processes may also produce more comprehensive understanding of complex problems, which could lead to more effective decisions, to the extent that a more holistic understanding of feedback loops is beneficial. However, these findings should be interpreted carefully. Even though aggregated cognitive maps such as those we analyzed are commonly interpreted as representations of shared knowledge and regarded as "social cognitive maps" (Gray et al., 2014), they are not equivalent to cognitive maps elicited directly from groups (e.g., in which participants work together to develop a cognitive map; Murphy et al., 2021). In such settings, cognitive maps would be shaped by participants' prior relationships, relative levels of authority and reputation, and personalities. Aggregating cognitive maps does not account for such social and behavioral influences. While our results indicate the possibility that collaborative settings facilitate cognition of feedback loops, future research is needed to assess how this finding bears out in real collaborative decision-making processes. In such studies, it would be particularly important to not only assess how group size affects systems thinking, but also how group size affects transaction costs of the decision-making process itself, which has implications for the scope and scale of decisions reached in collaborative settings (Casari and Tagliapietra, 2018; Fischer and Schläpfer, 2017; Koontz and Johnson, 2004).

Our finding that stakeholders perceive environmental trends to contribute to amplifying feedback loops and environmental shocks to self-regulation highlights the need for a more nuanced understanding of

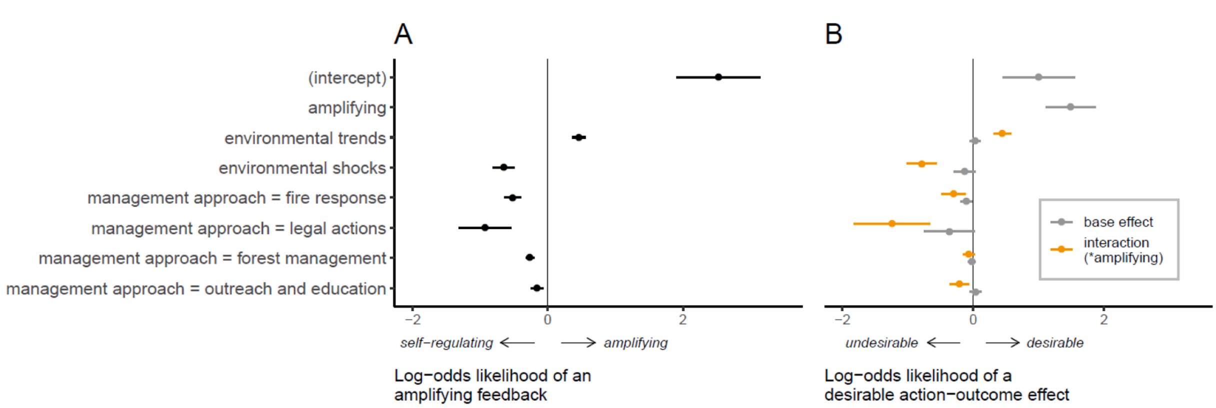

Fig. 5. Results from Bayesian multilevel statistical models. Models predict the likelihood that a perceived feedback loop is (A) amplifying rather than self-regulating and (B) desirable rather than undesirable, as a function of the classes of factors that comprise it. For example, "environmental trends" measures whether perceived feedback loops include factors classified as environmental trends (e.g., "juniper encroachment"). In addition to the set of factors included in model A, model B also includes an indicator of whether the feedback loop is amplifying as well as interaction terms that measured whether feedback loops are both amplifying and contain each class of factor.

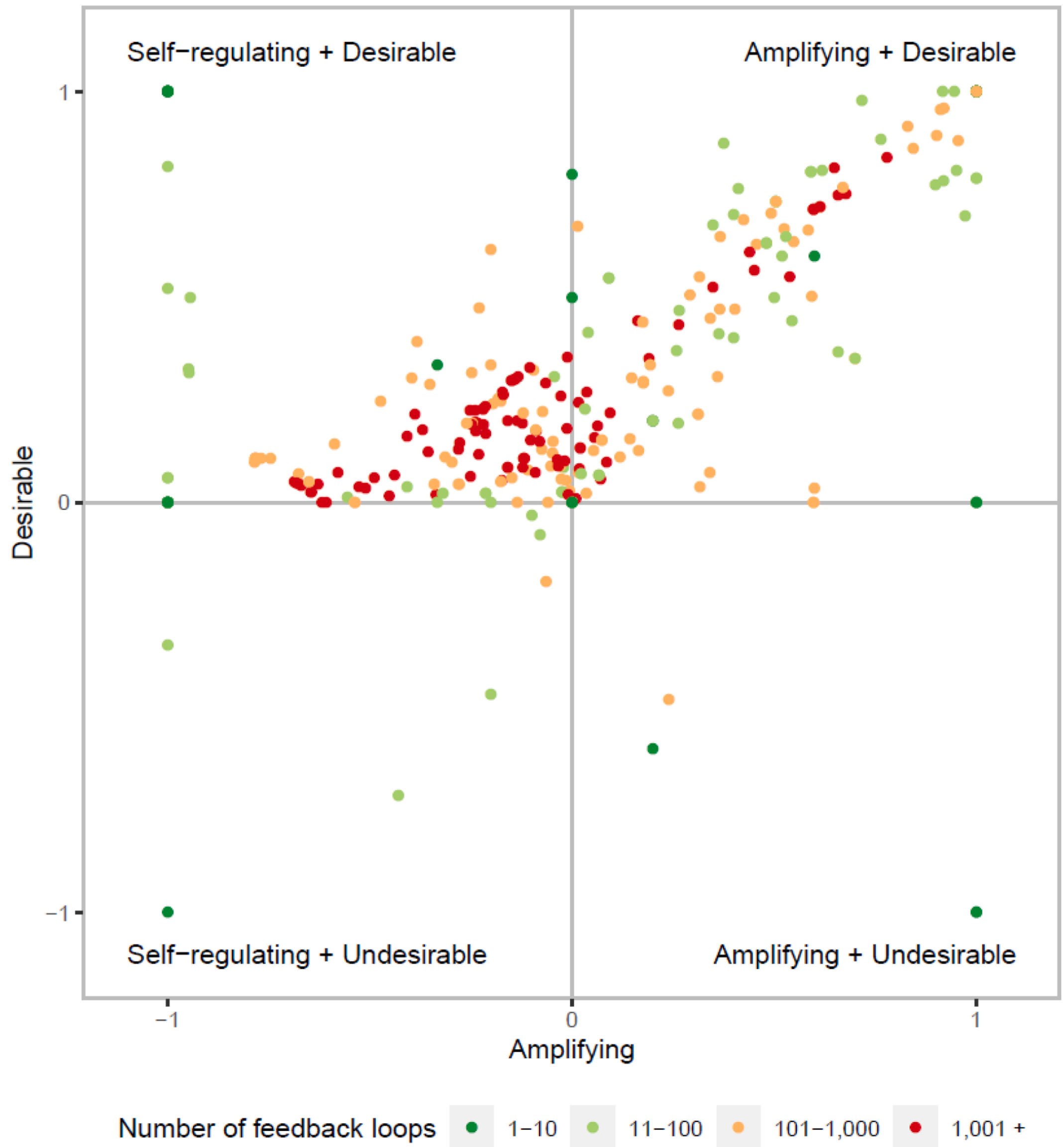

Fig. 6. Tendency for cognitive map factors to be featured in amplifying/self-regulating as well as desirable/undesirable feedback loops. Each point represents a factor (e.g., "suppression of wildfire"; "smoke impacts"). Points are colored according to the number of feedback loops in which they appear.

the "risk paradox" (Steelman, 2008; Wachinger et al., 2013), in which environmental trends (e.g., fuel accumulation) and shocks (e.g., devastating wildfires) both contribute to policy responses that amplify risk (e.g., preference for fire exclusion and suppression, which encourage fuel accumulation and high-severity fires). Our finding that stakeholders tend to perceive that self-regulating feedback loops are driven by environmental shocks deviates from the narrative that fire begets fire, via ever-higher commitments to suppression and resulting fire deficits, which in turn increase the likelihood of high-severity fires that escape initial containment (Parks et al., 2015). While this amplifying feedback loop certainly operates within our study system and appeared in stakeholders' cognitive maps, stakeholders documented numerous self-regulating feedback loops involving fire as an environmental shock. As an example, stakeholders observed that exposure to a fire could serve as a wake-up call, spurring investment in fuels reduction and other risk mitigation efforts, which in turn reduced exposure to fire. It is also plausible that due to the legacy of wildfire suppression and the corresponding narrative around the intractability of reforming fire management (North et al., 2015), stakeholders may be more attentive to the impacts of fires on human dimensions of wildfire governance rather than long-run fire risk itself. In particular, stakeholders may perceive the governance system to exist in a basin of attraction in which multitudes of self-regulating feedback loops involving short-term psychological, social, and management responses to fire events operate alongside a smaller number of amplifying feedback loops that increase hazard conditions over time.

Indeed, our findings highlight the need for greater nuance in our understanding of the challenge of wildfire risk governance, which typically focuses on these undesirable amplifying feedback loops (Calkin et al., 2015; Fischer et al., 2016a). Such feedback loops indeed appeared in stakeholders' cognitive maps. For example, stakeholders observed that suppression of wildfire decreases the resilience of forests to high-severity fire (e.g., via accumulation of flammable vegetation), which in turn prompts managers to commit greater resources to suppression (Fig. 1, bottom right). However, such undesirable amplifying feedback loops are the least common among the four classes of feedback loops depicted in Fig. 1, comprising only 12% of all feedback loops in our data. Of the four classes, desirable amplifying feedback loops were the most common (34%), followed by desirable self-regulating feedback loops (28%) and undesirable self-regulating feedback loops (26%). As an example of an amplifying desirable feedback loop, stakeholders perceived that active management of forests (e.g., application of harvesting, stand improvement, and/or prescribed fire, among other practices) facilitate increases in revenue from forest products, which in turn boosts capacity for fuels reduction (e.g., by subsidizing the cost of removing small diameter vegetation), thereby increasing the scope of active management (Fig. 1, top right). As an example of a desirable self-regulating feedback loop, stakeholders observed that the implementation of mitigation measures around homes can reduce the likelihood of damages from fire, which can in turn decrease landowners' appreciation of wildfire risk, and by extension their investment in mitigation measures (Fig. 1, top left). As an example of an undesirable self-regulating feedback loop, stakeholders described how smoke from prescribed burning negatively affects air quality, thereby reducing public tolerance for the use of fire for forest management, which in turn limits application of prescribed burning (Fig. 1, bottom left).

As our data do not measure the magnitudes of relationships among causal factors, our analysis cannot account for the relative strengths of perceived feedback loops. It is important to acknowledge the possibility that many feedback loops may have only modest effects on system outcomes and that, correspondingly, a limited number of loops may have disproportionately large influence. For example, it is certainly possible that a small number of undesirable amplifying feedbacks have outsized influence on the system dynamics. Future research that measures the magnitudes of causal relationships in cognitive maps could provide important insights into the relative influences of different classes of feedback loops. However, to the extent that fire-prone social-ecological systems such as our study region exist in undesirable basins of attraction characterized by high costs of risk mitigation and high levels of environmental hazards, our analysis suggests that the large number of *desirable* feedback loops are responsible. For example, the factor "air quality" tends to be featured in amplifying-desirable feedback loops, meaning that actions that limit impacts on air quality (e.g., restricting prescribed burning) reinforce themselves. One interpretation of such findings is that reforming wildfire risk governance will generally require policies that are sufficiently comprehensive so that they can disrupt the numerous micro-level feedback loops that favor existing management practices. Alternatively, such findings suggest the existence of leverage points and, correspondingly, the prospects for more targeted interventions that "work with" feedback loops (Biggs et al., 2015). For example, the prominence of air quality as a valued outcome in desirable amplifying feedback loops underscores the need to conduct forest and fire management planning processes in ways that robustly engage public health stakeholders, including advocacy groups, health care practitioners, and air quality regulators. Such strategies for collaborative decision-making could enable dialogue about how the dual objectives of protecting air quality and the increasing the use of prescribed fire for fuels reduction may or may not constitute a trade-off. In particular, planners and policy-makers could explore the possibility of integrating air quality regulations with fire management planning, as an interdisciplinary group of fire management and public health experts has recently proposed (Bowman et al., 2018). Such efforts to change institutions or otherwise alter system dynamics may be more feasible when systems are more susceptible to intervention (Biggs et al., 2015). In the context of fire-prone social-ecological systems, the prospects for intervention may be particularly high during periods following significant wildfire events themselves, which can spur stakeholders to rethink wildfire governance and undertake transformative policy changes (Nikolakis and Roberts, 2021).

Top-down implementation of forest and fire management in the U.S. West has created a legacy of risk-prone social-ecological forest systems. Collaborative, multi-stakeholder wildfire risk governance has gained recognition as an effective policy model, yet it remains under-funded and not well-integrated into large-scale forest management. Although we measured group cognition using aggregate cognitive maps rather than cognitive maps elicited from groups of stakeholders engaged in collaborative decision-making processes, our findings suggest that processes may not only spur recognition of potential wildfire system feedbacks but may also play an important role in uncovering the multitudes of individual feedback loops that contribute to the current stable state of high wildfire risk in the U.S. West. Acknowledgement and integration of systems thinking in wildfire management that accounts for micro-scale processes may indeed prove important to shift the system to a state of reduced risk.

CRediT authorship contribution statement

Matthew Hamilton: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing. **Jonathan Salerno:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Alexandra Paige Fischer:** Conceptualization, Funding acquisition, Investigation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

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