Cognition of complexity and trade-offs in a wildfire-prone social-ecological system

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Abstract

Wildfire risk is a defining environmental challenge throughout much of the American West, as well as in other regions where complex social and ecological dynamics defy simple policy or management solutions. In such settings, diverse forms of land use, livelihoods, and accompanying values provide the conditions for trade-offs (e.g. between protecting homes from uncontrollable fires and restoring low-severity fire to ecosystems as a natural disturbance process). Addressing wildfire risk requires grappling with these trade-offs at multiple levels—given the need for action by individuals as well as by large and diverse stakeholder groups—and under conditions of considerable complexity. We evaluated how individual and collective perception of trade-offs varies as a function of complexity through analysis of the cognitive maps—representations of perceived causal relationships among factors that structure an individual’s understanding of a system—of 111 stakeholders in the Eastern Cascades Ecoregion of central Oregon. Bayesian statistical analysis revealed a strong tendency against perception of trade-offs in individual maps, but not in a collective map that resulted from the aggregation of all individual cognitive maps. Furthermore, we found that lags (the number of factors that mediated the effect of an action on multiple valued outcomes) limited perception of trade-offs. Each additional intervening factor decreased the likelihood of a trade-off by approximately 52% in individual cognitive maps and by 10% in the collective cognitive map. However, the heterogeneity of these factors increased the likelihood of perception of trade-offs, particularly among individual cognitive maps, for which each unit increase of the Shannon diversity index translated into a 20-fold increase in the likelihood of perception of trade-offs. Taken together, these results suggest that features of complexity have distinct effects on individual—and collective-level perception of trade-offs. We discuss implications for wildfire risk decision-making in central Oregon and in other complex wildfire-prone social-ecological systems.

1. Introduction

We evaluate how stakeholders conceptualize trade-offs associated with wildfire risk management in a region of the American West where the interplay between environmental and social change not only contributes to wildfire risk, but also complicates efforts to mitigate it (North et al 2015, Fischer et al 2016a). As western landscapes become increasingly economically and culturally heterogeneous, the outcomes of wildfire risk mitigation decisions can affect a correspondingly broader set of values (Paveglio et al 2018), resulting in greater potential for trade-offs. Land managers and other actors who undertake or influence decisions about wildfire risk mitigation actions must acknowledge and address trade-offs (Moritz et al 2014, Wood and Jones 2019). However, trade-offs can be obscured by complex interactions among physical, biological, social, political, and economic processes that operate across multiple spatial and temporal scales. Against this backdrop, we evaluate how stakeholders perceive trade-offs by investigating three related questions:
1. Which actions and valued outcomes are most prone to perceived trade-offs?

2. How does complexity shape perception of trade-offs?

3. How does perception of trade-offs vary between individual and collective levels?

We adopt a novel methodological approach that applies network science and Bayesian statistical modeling to the analysis of cognitive maps—representations of perceived causal relationships among factors that structure an individual’s understanding of a system (Kosko 1986, Gray et al 2014). These cognitive maps depict potential trade-offs as instances in which an action (e.g. prescribed fire) generates effects on desirable features or qualities, which we term ‘valued outcomes’ (e.g. air quality, reduced risk to homes). Trade-offs involve a beneficial effect on one valued outcome and an adverse effect on another. Typically, these effects are mediated by multiple intervening factors. Accounting for these factors allows us to evaluate how perception of trade-offs varies as a function of the heterogeneity of causal pathways that link actions to outcomes (e.g. the degree to which pathways span biological, physical, social, economic, political and other types of factors) as well as the degree to which pathways feature lagged effects (i.e. number of intervening factors between actions and outcomes). Furthermore, by aggregating individual cognitive maps into a ‘collective cognitive map’, we evaluate of how trade-offs emerge as a function of how individuals independently and jointly perceive dynamics that contribute to wildfire risk.

Our empirical context, the Eastern Cascades Ecoregion (ECE) in central Oregon, provides an ideal setting for studying cognition of wildfire risk. The ECE features considerable social-ecological complexity and has experienced significant increases in wildfire risk over the last several decades (Spies et al 2014). Wildfire risk mitigation can be conducted by individual private landowners, but often requires collective action by multiple stakeholder groups on municipal, state, and federal lands. Consequently, the ECE offers a natural laboratory to investigate individual- and collective-level perception of trade-offs in a complex social-ecological system. Insights about factors that shape perception of trade-offs can contribute to more effective collaborative governance within the ECE, as well as other wildfire-prone settings throughout the American West and internationally.

2. The importance of understanding trade-offs in wildfire-prone social-ecological systems

Trade-offs are important in any decision-making context that features multiple objectives (Kahneman et al 1982), including environmental management (Campbell et al 2010, Farzan et al 2015, Cord et al 2017). Wildfire management in particular presents many opportunities for trade-offs, given the numerous and diverse resources and services that are valued in fire-prone forests (McLennan and Eburn 2014, Moritz et al 2014, Wood and Jones 2019). An active literature has highlighted how forest and fire management practices can give rise to trade-offs (table 1). Navigating these types of trade-offs is a necessary and challenging task for land managers and other stakeholders working to address wildfire risk (Ager et al 2017, Spies et al 2017).

Despite sophisticated approaches for evaluating multiple objectives in the management of wildfire-prone landscapes (e.g. Hand et al 2015, Ager et al 2017), there is limited understanding of how diverse stakeholders perceive the trade-offs associated with potential risk mitigation approaches. Addressing this gap is important for several reasons. First, an

| Management action | Valued outcomes affected positively by management action | Valued outcomes affected negatively by management action | Reference(s) |
|-------------------|--------------------------------------------------------|--------------------------------------------------------|-------------|
| Harvest prescriptions | Timber harvest volume | Reduction of wildfire risk to human communities | (Ager et al 2019) |
| Thinning | Timber production; habitat for white headed woodpeckers | Habitat for northern spotted owls; carbon sequestration | (Spies et al 2017) |
| Prioritizing restoration treatments to optimize revenue | Revenue from restoration treatments | Reduction of wildfire risk to human communities from national forest-ignited wildfires | (Ager et al 2017) |
| Thinning from above | Tree size complexity | Abundance of large trees | (Bradford and D’Amato 2012) |
| Suppression of naturally-ignited fires in wilderness areas | Reduction of wildfire risk to human communities; protection of habitat for certain sensitive species | Ecosystem structure and function in wilderness areas | (Miller et al 2011) |
understanding of trade-offs can improve policy design. Basic awareness of trade-offs can facilitate the types of decisions that avoid unintended consequences (Anderies et al 2004, Larrosa et al 2016). Second, appreciation of trade-offs can facilitate buy-in or compliance when such awareness leads stakeholders to appreciate that decisions must account for objectives besides their own (Gregory et al 2012, Bessette et al 2017). Finally, stakeholders’ perceptions of the dynamics that comprise a complex social-ecological system (including the trade-offs embedded in those dynamics) are more than ‘just’ perceptions. Stakeholders have agency within these systems, and their beliefs shape their actions, with implications for valued outcomes resulting from both individual- and collective-level environmental management behaviors (Ajzen 1991, Beratan 2007, Klöckner 2013).

Correspondingly, understanding the factors that contribute to perception of trade-offs can improve decisions and decision-making processes. For example, decision-makers who are aware of conditions that can obscure trade-offs may be more likely to explore the possibility of unintended consequences of preferred actions. Likewise, in collaborative decision-making settings, facilitators who can anticipate situations in which participants are more likely to identify numerous trade-offs may be better equipped to manage expectations about the efficiency of decision-making processes.

2.1. Perception of trade-offs in complex social-ecological systems

Although policy-makers and researchers often strive to identify and promote win-win solutions that produce desirable outcomes while avoiding adverse consequences, it is increasingly recognized that such solutions may overlook trade-offs (Campbell et al 2010, Daw et al 2015). Research on cognition suggests that individuals may have difficulty perceiving trade-offs in complex systems (Sterman 1994, Meadows 2008, Galafassi et al 2017).

In particular, research suggests that processing diverse types of information creates a cognitive burden (Iselin 1988, Ploetzner et al 2001, Harper et al 2009) and that ‘boundedly rational’ individuals are more likely to make judgments based on knowledge of one domain rather than many (Hibbard and Peters 2003). This tendency may inhibit consideration of how actions affect a range of distinct processes. For example, outcomes of wildfire risk mitigation decisions are shaped by dynamics that may span biological, physical, social, economic, and political factors (Spies et al 2014, Steelman 2016). The diversity of factors that mediate the pathways by which actions affect valued outcomes can amplify uncertainty and may present more opportunities for unintended adverse effects (Spies et al 2014). Anticipating or avoiding such outcomes requires grappling with trade-offs, which in turn may depend on the degree to which stakeholders’ understanding of system dynamics integrates diverse sets of knowledge (Galafassi et al 2017).

Perception of trade-offs may likewise be limited when outcomes do not directly result from actions. For example, research shows that individuals are more attentive to short-term responses over long-term responses (Dörner 1990, Ullah and Kane 2010, Sterman 2012). In complex social-ecological settings, considerable time may elapse between human activities and the realization of a hazard event (Liu et al 2007, Steen-Adams et al 2017, Fischer 2018). As lags increase, so too may the prospects for actions to result in unintended side effects. For example, in wildfire-prone landscapes, forest and wildfire management practices such as wildfire exclusion often emphasize short-term risk reduction, which may in turn contribute to hazard conditions over the long-term as flammable vegetation accumulates (North et al 2015, Fischer et al 2016a).

2.2. How cognitive maps reveal perceived trade-offs

A useful approach for understanding how people perceive complex social-ecological dynamics is the elicitation of cognitive maps (figure 1(A)). Cognitive maps depict mental models, which in turn represent how individuals make sense of the world around them by acquiring and testing assumptions about causal relationships among states of affairs, concepts, or other factors (Gaie 1967, Byrne and Johnson-Laird 2009). Because cognitive maps can explicitly represent the linkages among diverse sets of factors that characterize complex systems, they have been utilized extensively in research on the dynamics that shape social-ecological systems, including wildfire-prone landscapes (Zaksek and Árvai 2004, Zhang and Letten 2016, Walpole et al 2017).

Cognitive maps are often depicted and analyzed as networks composed of causal linkages among factors (figure 1(B)). This network perspective in turn enables measurement of how people perceive dynamics that span multiple factors. Specifically, any instance in which an action affects two valued outcomes creates the conditions for a potential trade-off. Trade-offs occur when an action generates a beneficial effect on one such outcome and adversely affects the other, while synergies result from beneficial effects on both valued outcomes (figure 1(C)). Cognitive maps likewise allow for measurement of the degree to which the causal chains that comprise trade-offs feature heterogeneous sets of factors (figure 1(D)) as well as the degree to which action-outcome chains feature lagged effects (figure 1(E)). It is important to note that while such lags do not directly measure the time or distance that separates an action from its outcome (as in ‘spatial lags’ or ‘temporal lags’), we use the term ‘lags’ to similarly refer to the (non)immediacy of causal
relationships, which can be measured using the network concept of ‘path length.’

2.3. Individual/collective perception of trade-offs

Wildfire-prone landscapes are inhabited by people who prioritize different values (Paveglio et al 2018) and may, as individuals, conceptualize wildfire risk and risk mitigation distinctly. Consequently, individual-level cognition of the pathways by which risk mitigation actions affect valued outcomes has important implications for collective-level perception of trade-offs. For example, given a particular management action, one individual may be aware of its effect on one valued outcome, while another individual may be aware of its effect on another (Beratan 2007). Research has identified conditions under which the ‘wisdom of the crowd’—i.e. collective cognition among groups of people who do not necessarily interact—can outperform the individual-level cognition (Galton 1907, Krause et al 2010, Freitag et al 2019). For example, Krause et al (2010) asked members of the public to estimate the number of marbles in a jar; subsequently, respondents were asked to estimate the number of consecutive ‘heads’ outcomes of coin tosses would approximate the likelihood of winning the German lottery. The mean value of responses to the first question was extremely close to the correct value, while the mean value of responses to the second question was far from the correct value, illustrating the difference between tasks that tolerate high imprecision (e.g. estimating a count of marbles), and tasks that require expert judgment (e.g. equating probabilities). However, the task of estimating values is distinct from the task of describing system dynamics, and the conditions under which stakeholders—individually as
well as collectively—perceive trade-offs has received limited attention.

3. Methods

3.1. Study system

We investigated perception of trade-offs related to wildfire risk mitigation in the Eastern Cascades Ecoregion (ECE) of Oregon (figure 2). Dry mixed conifer forests extend over much of the study area. The crest of the Cascades defines the western boundary of the ECE, where cooler and wetter subalpine forests are dominant. The eastern portion of the ECE is characterized by shrub steppe. The study system is a mosaic of public, private, and tribal lands, which are managed by federal and state agencies, tribal governmental organizations, corporations, and individuals.

Like many regions of the western US, wildfire risk has sharply increased within the ECE. Large-scale and uncontrollable ‘megafires’ have become increasingly common, driven in part by changing climatic conditions and accumulation of fuels as a result of long-standing wildfire suppression policies (Aubry et al 2011, Chmura et al 2011). In response, stakeholders that manage land have sought to reduce wildfire risk through increased investment in forest and wildfire management. Stakeholders also include representatives of organizations that do not manage lands or bear responsibility for wildfire response but seek to influence forest or wildfire management through advocacy and participation in multi-stakeholder decision-making processes (Davis et al 2012). For example, the ECE features numerous task forces, steering committees, and other collaborative decision-making groups.

3.2. Data collection

During November 2017–March 2018, we collected data on wildfire risk cognition using cognitive mapping exercises paired with a semi-structured interview, which was approved by the University of Michigan Institutional Review Board (ID: HUM00133263). Our study population was defined as the set of individuals who had been identified as key stakeholders in a study on wildfire risk in the ECE that was conducted in 2011–2013. Specifically, participants of the prior study identified these individuals as people with whom they had interacted in the past five years to collaborate, seek information, provide advice, or influence in the context of wildfire response or wildfire-prone forest management (Fischer et al 2016b). To optimize the diversity of our sample in terms of geographic affiliation as well as stakeholder identity, we stratified our population by geographic region of interest as well as their main affiliation (e.g. federal agency, non-governmental organization, private forest owner) and randomly selected individuals across these strata for recruitment in the current study. Participants were recruited by email and phone to schedule meetings, typically at their place of work or a public location.
Table 2. Examples of factors classified as actions and valued outcomes.

| Factor class     | Factor subclass                        | Example factor                                                                 |
|------------------|----------------------------------------|-------------------------------------------------------------------------------|
| Action           | Fire response                          | Aggressive initial response to fire                                          |
|                  | Forest management                       | Create fuel breaks                                                            |
|                  | Legal                                   | Use of ESA (Endangered Species Act) by conservation groups                   |
|                  | Outreach and education                  | Education about role of wildfire in ecosystem                                |
| Valued outcome   | Aesthetic                               | Scenic value                                                                  |
|                  | Air quality                             | Limit smoke impacts from prescribed fire                                    |
|                  | Cultural and historic                   | Cultural resources protected during project implementation                   |
|                  | Firefighter safety                      | Safety of firefighters                                                         |
|                  | General environmental quality           | Limit carbon emissions                                                         |
|                  | General wildfire risk reduction         | Limit adverse impacts of wildfire                                             |
|                  | Local economies                         | Strong local economies                                                         |
|                  | Protection of flora                     | Old growth                                                                     |
|                  | Protection of property                  | Limit homes lost                                                               |
|                  | Public safety                           | Safety of residents                                                            |
|                  | Ranching                                | Short-term expenses after fire for cattle owners                              |
|                  | Recreation                              | Snowmobile access                                                              |
|                  | Timber                                  | Revenue from sawlogs                                                           |
|                  | Water quality                           | Stream water quality                                                           |
|                  | Wildlife habitat                        | Spotted owl habitat quality                                                    |

In each cognitive mapping exercise, individuals identified factors related to wildfire risk as well as the relationships by which they considered those factors to be causally linked. We used MentalModeler software (Gray et al. 2013), which allowed participants to depict these factors and linkages visually. Participants were prompted to identify factors that could be conceptualized as quantitative variables (e.g., ‘forest quality’, rather than ‘forest’) which in turn enabled participants to specify the sign of each causal effect (positive or negative, i.e. increasing or decreasing). A total of 111 individual cognitive maps were collected.

3.3. Creating the collective cognitive map and classifying factors

We created a single collective cognitive map by aggregating all individual maps (Özesmi and Özesmi 2004, Gray et al. 2012). Specifically, factors featured in multiple individual maps functioned to link these maps. This approach required the identification and consolidation of factors that referred to the same phenomena, e.g. ‘prescribed fire’ and ‘prescribed burning’. To structure this process, we classified factors (for details see appendix A), which also enabled us to identify ‘action’ and ‘valued outcome’ factors featured in potential trade-offs (table 2). Factors were coded as actions if they represented fire response, forest management, legal, or outreach/education strategies. Factors were coded as valued outcomes if they referred to effects on desirable features or qualities (additional classes are described in appendix A).

3.4. Measuring trade-offs and synergies in cognitive maps

Our unit of analysis was instances of potential trade-offs, which we operationalized as network configurations in which an ‘action’ node affected two ‘valued outcome’ nodes. Consequently, our dependent variable—perception of trade-offs—took the value of 1 when the action node resulted in a positive effect on one valued outcome node and a negative effect on the other, and 0 otherwise (i.e., a perceived synergy). Rarely did actions affect both valued actions directly. Indeed, a key advantage of analyzing cognitive maps as networks was that this approach allowed us to measure the indirect pathways by which actions affected valued outcomes via intermediate factors. Specifically, we used the ‘All_Simple_Paths’ algorithm in the Python language package NetworkX (Hagberg et al. 2008) to identify action-outcome pathways. Given subsets of source and target nodes (in our case, action and valued outcome nodes), this algorithm returns a list of all paths from all source nodes to all target nodes. We focused on the subset of paths with no more than five linkages. We measured whether each path resulted in a cumulatively positive or negative effect by calculating the product of all causal linkages between nodes that comprise the path (e.g., given A (+) B (−) C (−) D), 1−−−1 = 1, a cumulatively positive effect). It is important to distinguish this approach from how feedback loops are measured in cognitive maps and related systems models (e.g., causal loop diagrams). In particular, while feedback loops are cyclic (e.g., A → B → C → A), the chains that comprise trade-offs are acyclic. Consequently, chains with cumulatively positive or negative effects are not

5 The number of additional paths of length n increases sharply with each unit increase in n, before declining at high values of n. Likewise, the number of possible trade-offs scales as the square of paths that originate from the same node. We set a threshold at n = 5 in order to capture sufficient variation in the heterogeneity of intervening factors within potential trade-offs, but without measuring an excessively large number of potential trade-offs. Model results were similar for datasets generated using threshold values of n = 3 and 4.
responsible for amplifying or self-regulating dynamics, respectively (though they may be embedded in feedback loops).

We calculated perceived trade-offs and synergies for all individual cognitive maps as well as the collective cognitive map. Because the collective map was the aggregation of individual maps, all trade-offs and synergies present in the individual maps were also present in the collective map. In this sense, if a trade-off involving a particular pair of valued outcomes in one individual’s map was balanced by a synergy involving the same pair in another individual’s map, this dynamic would be conserved in the collective map as well. However, because the collective map included sets of causal pathways that spanned multiple individual maps, it presented numerous additional opportunities for trade-offs and synergies. Importantly, while aggregation itself did not affect the tendency for potential trade-offs to be realized as trade-offs or synergies in the collective map (relative to individual maps), emergent properties of the collective map (e.g. related to causal pathways) had implications for the balance of trade-offs and synergies as well as the degree to which the tendency for trade-offs varied depending on the heterogeneity and lagged nature of potential trade-offs.

We measured heterogeneity as the Shannon index of the diversity of parent classes of intervening factors (e.g. in figure 2(D), the top configuration, with five different classes represented once, is more heterogeneous than the bottom configuration, in which all intermediary factors belong to the same class). We measured lags as the total number of linkages from each action to each pair of valued outcomes (e.g. in figure 2(E), the top configuration features nine linkages, while the bottom features three). We applied this methodology to the individual and collective cognitive maps.

Processing the large number of potential trade-offs from the collective cognitive map proved to be computationally challenging. We therefore drew a random sample of 5000 potential trade-offs from the collective cognitive map. This sample, together with all potential trade-offs from the 111 individual cognitive maps, comprised the observations to which we fit respective statistical models. Smaller samples (e.g. 2000) and larger samples (e.g. 20 000) produced nearly identical statistical model results.

3.5. Regression models
We fit Bayesian multilevel binomial regression models to evaluate how characteristics of cognitive map networks are associated with perception of trade-offs. 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 can be operationalized into statements of the likelihood of observing a trade-off as a function of the additive contribution of multiple cognitive factors. We term each of these observations instances. This representation is fundamentally about the odds of observing a trade-off, which dictated the use of a binomial logistic model. We used multilevel architecture because of the hierarchical structure of our data (Gelman and Hill 2007, McElreath 2015), with each instance assigned to multiple groupings for represented actions (e.g. create fuel breaks; education about role of wildfire in ecosystem) and paired valued outcomes (e.g. limit smoke impacts from prescribed fire, economic benefits from salvage logging), to control for variance clustered around each factor of each group. The individual cognitive map network data were additionally clustered by actor (i.e interview clustered respondent). Models were fitted to both individual (n = 2380) and collective (n = 5000) datasets (see appendix B for additional details, including formal model specification).

4. Results

4.1. What valued outcomes are most in conflict, and via which management actions?
While trade-offs were fairly uniformly common in the collective cognitive map, and were most prominently associated with aesthetic values and air quality, individual cognitive maps featured three general groupings of prominent trade-offs (figure 3). The first group involves wildlife. Valued outcomes within this category were featured in trade-offs with valued outcomes in 8 of the 14 other categories (bottom position of the y-axis, showing eight colored trade-offs with categories listed low to high on the x-axis). Another group involves air quality. Compared with valued outcomes related to wildlife, air quality outcomes were featured in trade-offs with fewer other value categories. However, air quality was involved in high proportions (>50%) of trade-offs with outcomes in two such categories—protection of flora and property. The third group involved trade-offs between outcomes of the same value category (e.g. air quality on both the x- and y-axes, for instance if prescribed burning reduces air quality in the near-term but also limits the risk of extremely poor air quality from a more intense fire in the future).

Although categories of values varied in their tendencies to be associated with trade-offs, we likewise found variance in the degree to which different types of actions prompted trade-offs, which additionally varied between the individual and collective cognitive maps (figure 4). For individual cognitive maps, actions that involved wildfire response were associated with the lowest proportion of trade-offs, followed by legal
actions, then forest management actions, and finally by actions related to outreach and education efforts. By contrast, in the collective cognitive map, wildfire response actions were most prone to trade-offs, followed by forest management, outreach/education, and finally legal actions.
4.2. How are trade-offs associated with complexity at the individual and collective level?

Intercept coefficient estimates correspond to the mean log-odds of a perceived trade-off, while controlling for other variables included in the models. Models indicated a strong tendency against perception of trade-offs in individual cognitive maps (figure 5). In the collective cognitive map, estimates were not credibly different from zero.

For individual as well as collective cognitive maps, trade-offs were more likely when they featured a higher heterogeneity of intervening factors (e.g. figure 2(D)). This effect was particularly pronounced when estimated using the individual cognitive map-level data, with a coefficient estimate of 3.00 (log-odds scale), which translates to approximately a 20-fold increase in the likelihood of a trade-off for each unit increase in the Shannon diversity index value of intervening factors, all else being equal.

Lags (figure 2(E)) decreased the likelihood of perception of trade-offs, particularly in the individual-level model where each additional intervening factor decreased the likelihood of a trade-off by approximately 52% in individual cognitive maps and by 10% in the collective cognitive map.

Perception of trade-offs was less likely, but not at a level of 95% credibility, when potential trade-offs featured valued outcomes of the same category (e.g. both related to air quality, or to firefighter safety).

5. Discussion

5.1. Individual/collective dynamics, complexity, and trade-offs

Our findings are broadly consistent with the idea that individual-level cognition typically encompasses only a sub-model of a complex system (Beratan 2007). Statistical models indicated a strong tendency against perception of trade-offs in individual cognitive maps, but not in the collective cognitive map, which suggests that the specialized knowledge of individual stakeholders does not enable a more complete understanding of unexpected or indirect outcomes of management actions. To the extent that perception of trade-offs reflects systems thinking (Galafassi et al 2017), these results highlight a gap between individual-level knowledge and the ‘wisdom of the crowd’, as revealed in the collective cognitive map.

We found that different measures of complexity have distinct effects on perception of trade-offs. At both the individual and collective levels of analysis, perception of trade-offs was more likely when action-outcome paths spanned a more heterogeneous set of intervening factors (e.g. not just relating to biophysical context, but also to institutional processes, demographic factors, the availability of assets, and so on). The relationship between heterogeneity and perception of trade-offs suggests that when stakeholders—independently or collectively—incorporate diverse sets of knowledge in their understanding of social-ecological dynamics, they are better able to perceive both desirable and adverse consequences of management actions. Prior research has highlighted the relationship between knowledge diversity and environmental governance outcomes (e.g. Roux et al 2006) and our results suggest that this relationship may be mediated in part by perception of trade-offs.

In contrast, lags reduce perception of trade-offs, particularly at the individual cognitive map level, which highlights the need for greater nuance in thinking about how this particular indication of complexity relates to trade-offs. In particular, a central premise of research on social-ecological systems is that lags, whether spatial or temporal, increase the likelihood of unintended (negative) outcomes resulting from actions designed to achieve a particular goal (Miyasaka et al 2017). That we show perception of trade-offs decreases with lags does not contradict this expectation. Rather, our models suggest that explicit causal pathways leading to trade-offs are more likely recognized when valued outcomes result more directly from actions.

5.2. Management implications

Taken together, these results have important implications for wildfire risk mitigation in the ECE, as well as in complex wildfire-prone landscapes throughout the American West and internationally. In particular, our analysis of how trade-offs are distributed among different pairs of valued outcomes highlights a gap between independent and collective perception of wildfire risk. The dominance of trade-offs related to wildlife in individual cognitive maps points to the need for greater awareness of the variety of ways in which management affects habitat for different species (Spies et al 2017). However, when individual cognitive maps are aggregated into a collective cognitive map, trade-offs involving aesthetic value and air quality are most prominent. Advocates of risk reduction actions that affect aesthetic values (e.g. which includes most forest management practices) should be attentive to variation in aesthetic preferences across socially diverse landscapes (Ribe 1989, Nay and Brunson 2013). In the case of trade-offs involving air quality, our results provide empirical support for what many decision-makers and other wildfire risk mitigation practitioners know from personal experience—stakeholders may not distinguish ‘bad’ smoke (e.g. from large-scale wildfires) from ‘good’ smoke (e.g. from prescribed fires that serve to reduce hazardous fuel loads) (Olsen et al 2014). To the extent that management actions necessary for mitigating wildfire risk also unavoidably generate smoke, our results highlight the importance of outreach and education strategies that forthrightly address smoke impacts in the broader context of wildfire risk reduction strategies. Indeed, we found that perceived trade-offs resulting from outreach and education actions
were particularly prominent; in a number of these trade-offs, outreach activities were perceived to encourage prescribed burning, which in turn was perceived to adversely affect certain values (e.g. air quality) while benefiting others (e.g. forest health).

Finally, our study highlights the value of collaborative decision-making processes while helping to explain one frustration of individuals who participate in such initiatives. In the ECE, groups such as the Deschutes Collaborative Forest Project, the Klamath Lake Forest Health Partnership, and Project Wildfire bring together diverse stakeholders to facilitate wildfire risk mitigation planning and decision-making. Such settings provide opportunities for stakeholders to expand their own mental models of wildfire risk while presenting their understanding of the pathways by which actions shape valued outcomes in ways that may not be appreciated by other stakeholders. In particular, our results suggest that wildfire risk mitigation planning processes that bring together diverse groups of individuals can provide a mechanism for combining individuals’ understanding of action-outcome pathways in ways that compel participants to come to terms with trade-offs that may not have been evident to them independently. Importantly, while such processes can enable decisions that are more ‘optimal’—in the sense that they more holistically evaluate trade-offs and have greater potential to avoid unintended consequences—they may do so at the expense of efficiency. However, our finding that perception of trade-offs increases in accordance with stakeholders’ ability to integrate heterogeneous knowledge suggests that collaborative decision-making processes need not involve protracted disagreement. If such processes can enable learning, and specifically exposure to new domains of knowledge (e.g. public health specialists gaining an appreciation of federal agency forest management project cycles, or timber industry representatives learning about outdoor recreation economies), our results suggest that groups and individuals may be more likely to appreciate trade-offs, which may in turn facilitate new forms of problem-solving (Galafassi et al 2017).

6. Conclusions

Recent research has emphasized the need to analyze wildfire risk governance as a social-ecological system, characterized by complex interactions among physical, biological, social, political, and economic processes (e.g. Calkin et al 2015, Steelman 2016, Fischer et al 2016a). This study demonstrates that certain features of complex systems—specifically the cognitive processes by which people perceive cause-and-effect relationships—can be measured and evaluated. Future research is needed to explore additional aspects of complexity such as feedbacks and emergent properties. Challenges facing the American West, such as invasive species and water resource allocation, presents clear opportunities for such research, and we propose that our approach has relevance across systems where environmental change compels individual and collective action.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available for legal and/or ethical reasons.

Appendix A. Methodology for classifying factors in cognitive map

Factors featured in individual cognitive maps were classified in order to (1) construct variables (e.g., related to actions and valued outcomes) and (2) enable individual models to be aggregated into a collective cognitive map.

The 111 individual cognitive maps contained 2718 uniquely named factors. A large number of these factors represented the same concept (e.g., ‘prescribed fire’ and ‘prescribed burning’). To methodically process the entire list of uniquely named factors, we first assigned each a parent class (table A1). Parent classes loosely aligned with variables featured in the sustainable livelihoods framework (Scoones 1998), which we selected based on its holistic focus on a range of social and ecological variables that characterize a complex system. For all factors in each parent class, we subsequently assigned each to one of 3–9 child classes. Finally, we reviewed all factors within each child class, and consolidated all that represented the same concept, which resulted in 1310 unique factors.

It is important to note that while ‘Action’ was a parent class, ‘Valued outcome’ was a child class, because only a subset of outcome factors related to values. Additionally, we further classified valued outcomes into 15 subclasses (e.g., ‘Aesthetic’, ‘Air quality’). Consequently, the main text text of the paper (e.g., table 2) refers to ‘Action’ and ‘Valued outcome’ as classes, and provides examples of subclasses for each (e.g., ‘Fire response’ for ‘Action’ and ‘Aesthetic’ for ‘Valued outcome’).
Appendix B. Methodology for statistical modeling

B.1. Statistical model estimation

Justification for our statistical modeling approach is stated in the main text. The multilevel binomial model predicting the odds of observing a trade-off in the individual cognitive map is specified as follows:

\[ p_i \sim \text{Binom}(1, p_i) \logit(p_i) = \alpha + \alpha_{\text{actor}[i]} + \alpha_{\text{outcome1}[i]} + \alpha_{\text{outcome2}[i]} + \beta_{\text{lag}} L_i + \beta_{\text{div}} D_i + \beta_{\text{class}} C_i \]

where a trade-off outcome, \( p_i \), for instance \( i \), is represented as a binomial function of one draw and probability \( p_i \). The Logit link of \( p_i \) is a function of a linear predictor; \( \alpha \) is the grand intercept; \( \alpha_{\text{actor}[i]} \) are the unique varying intercepts for each actor; \( \alpha_{\text{outcome1}[i]} \) are the unique varying intercepts for each first-outcome of a trade-off outcome pair; \( \alpha_{\text{outcome2}[i]} \) are the unique varying intercepts for each second-outcome of a trade-off outcome pair; \( \beta_{\text{lag}} L_i \) is the instance-level effect of lag; \( \beta_{\text{div}} D_i \) is the instance-level effect of diversity; \( \beta_{\text{class}} C_i \) is the instance-level effect of having both the first and second outcome of the trade-off outcome pair as members of the same child class. The statistical model fitted to the collective cognitive map data does not contain the \( \alpha_{\text{actor}[i]} \) term. The specification for the collective cognitive map is identical to the above. Each statistical model was fitted to the respective datasets describing the individual (\( n = 2380 \), complete network) and collective (\( n = 5000 \), subsampled from the complete network) cognitive maps.

Priors on all instance-level fixed effects are Gaussian, with mean of zero and standard deviation of one. Priors on all varying intercept effects are Gaussian.
with mean of zero and weakly regularized variance hyperparameters; priors on hyperparameters are half-Cauchy with location of zero and scale of one. Models are coded following McElreath (2015, p373) using the map2stan function in R. Model estimation is conducted in Stan, called through R (R version 3.5.1 (2018-07-02) “Feather Spray”, x86_64-apple-darwin15.6.0 (64-bit) platform; R Core Team 2018), which implements a Hamiltonian Monte Carlo procedure (rstan v2.18.1; Stan Development Team 2018). Diagnostics, including traceplots and kernel densities, confirmed adequate mixing (table B1, figure B1). Published model runs were completed with two chains, a 50,000-iteration burn-in, and 50,000-iteration posterior sample.

The 100,000-iteration model runs were estimated in approximately 223 min and 949 min, for the individual and collective cognitive maps, respectively. Processing was conducted on an Intel i9-7820X 3.6/4.5 GHz 8-core processor with 64 GB of 2400 MHz DDR4 memory running macOS High Sierra (v10.13.6).

Figure B1. Traceplots of statistical model simulation for (a) the individual cognitive map data and (b) collective cognitive map data.
B.2. Model diagnostics

Model estimation produced samples from the posterior distribution of all parameters specified in the main text. Coefficient estimates, their variance, and highest 95% posterior density interval (HPDI) are reported in Table B1. Diagnostics of both individual and collective models appear adequate. The number of effective samples (\(n_{\text{eff}}\)) are not substantially lower than the value of samples of the posterior distribution, indicating the chains are efficient (McElreath 2015, p 257). The Gelman–Rubin convergence diagnostic values are 1, indicating the chains have converged (Gelman and Rubin 1992). Examination of traceplots appear normal (figure B1). Posterior predictive checks were conducted using the postcheck() function (rethinking); observed data are reasonably contained within the prediction interval for both models.

| Coefficient | Mean | Standard deviation | Lower HDPI | Upper HDPI | \(n_{\text{eff}}\) | Rhat |
|-------------|------|--------------------|------------|------------|----------------|------|
| **Individual cognitive map** | | | | | | |
| Intercept | −2.49 | 0.72 | −3.90 | −1.07 | 43597 | 1 |
| Heterogeneity | 3.00 | 0.54 | 1.95 | 4.05 | 28175 | 1 |
| Lag | −0.74 | 0.12 | −0.97 | −0.51 | 14512 | 1 |
| Same value category | −0.57 | 0.39 | −1.33 | 0.18 | 54062 | 1 |
| **Collective cognitive map** | | | | | | |
| Intercept | −0.26 | 0.50 | −1.25 | 0.70 | 60457 | 1 |
| Heterogeneity | 0.26 | 0.12 | 0.03 | 0.49 | 127170 | 1 |
| Lag | −0.10 | 0.05 | −0.20 | 0.0 | 65861 | 1 |
| Same value category | −0.10 | 0.10 | −0.30 | 0.10 | 129829 | 1 |

Table B1. Coefficient estimates, variance, 95% highest density posterior interval (HPDI), approximate number of effective samples (\(n_{\text{eff}}\), and approximate convergence of Markov chains to the target distribution (Rhat).

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