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Advancing Collective Decision-Making Theory with Integrated Agent-Based Modeling and Ethnographic Data Analysis: An Example in Ecological Restoration

Abstract

Ecological restoration actions generally result from collective decision-making processes and can involve diverse, at times contentious, views. As such, it is critical to understand these processes and the factors that might influence the resolution of diverse perspectives into a set of coordinated actions. This paper describes the adaptation and calibration of a stylized collective decision-making agent-based model using ethnographic data, to advance theory on how decisions emerge in the context of ecological restoration in the Chicago Wilderness. The prototypical model provided structure and organization of the empirical data of two Chicago Wilderness member groups and revealed organizational structures, patterns of interactions via formal and informal meetings, and parameter values for the various mechanisms. The organization of the data allowed us to identify where our original model mechanisms required adaptation. After model modifications were completed, baseline scenarios were contrasted with observations for final parameter calibration and to elaborate explanations of the study cases. This exercise allowed us to identify the components and mechanisms in the system to which the outputs are most sensitive. We constructed relevant hypothetical scenarios around these critical components, and found that key liaisons, agents with high interaction frequencies and high mutual respect values are useful in promoting efficient decision processes, but are limited in their ability to change the collective position with respect to a restoration practice. Simulations suggest that final collective position can be changed when there is a more equitable distribution of agents across groups, or the key liaison is very persuasive (i.e. interacts frequently and is highly respected) but is non-reciprocal (i.e. does not respect others highly). Our work advances our understanding of key mechanisms influencing collective decision processes and illustrates the value of agent-based modeling and its integration with ethnographic data analysis to advance the theory of collective decision making.

Keywords:
Collective Decision-Making, Ethnographic Data, Ecological Restoration, Empirical Modeling

Introduction

1.1 Ecological restoration is "the process of assisting the recovery of an ecosystem that has been degraded, damaged, or destroyed" (SER 2004, p.1). Although the overarching goal of restoration is to enhance the health, integrity, and sustainability of natural ecosystems, the process is driven by human intervention. Because restoration actions generally result from collective decision-making processes that can involve conflict among actors within environmental organizations (Gobster & Hull 2000), it is critical to understand how restoration decisions are made, and what factors might influence the resolution of diverse perspectives into a set of coordinated actions. Following the work of Arrow et al. (2000), we view the groups involved in restoration decision-making as complex adaptive systems. These groups are characterized by multiple forms of interaction among group members and by the influence of the socio-economic and political context in which the group is embedded. The dynamics created by interpersonal interactions and the influx of information and resources from outside of the group result in decision-making processes that affect ecological restoration decisions. Several common patterns of collective decision making outcomes have been identified in the literature (Arrow et al. 2000; Kerr & Tindale 2004; Ohtsubo & Masuchi 2004; Franks et al. 2013). Explaining how these patterns emerge would therefore contribute towards advancing the theory of collective decision-making.

1.2 To explore the process of group-decision making in the context of ecological restoration, we integrate a stylized agent-based model of collective decision-making with analysis of ethnographic data from two specific cases of ecological restoration in the Chicago Wilderness, "a regional biodiversity conservation alliance committed to protecting nature and enriching the lives of the region's residents" (Heneghan et al. 2013). The stylized agent-based model of collective decision-making (Watkins et al. 2013) was informed by theories of collective decision-making and individual psychology, as well as data from in-depth, qualitative interviews and participant observation of a multi-case study of organizations conducting ecological restoration in the Chicago region. For this study, we adapted and calibrated the prototypical model with data from two case-specific scenarios of collective decision-making processes. The initial model helped us structure and understand our empirical data, and in turn the analysis of our empirical data helped refine our initial conceptualization of the collective decision-making process. Through this study, we identify critical components and processes of the collective decision-making process that explain a range of management styles and corresponding decision outcomes, providing insights into how collective positions change or remain stable over time. We also highlight the ways in which simulation models and empirical data analysis inform each other, and illustrate how this integrated exercise advances our understanding of collective decision-making processes in general and in the context of urban ecological restoration in particular. Below, we briefly review the literature on collective decision-making and the relevance of agent-based modeling (ABM) in this area of inquiry, as well as the importance of integrating ethnographic data into the modeling process.

Collective decision-making

1.3 In general, a collective decision-making system can be viewed as being comprised of (i) the positions, goals, beliefs, and/or preferences of agents, (ii) the capabilities of agents to influence the positions, preferences, or opinions of other agents and/or the final decision outcome, (iii) interpersonal interactions and the group context that emerges from these interactions, and (iv) the broader context in which a group is embedded (Arrow et al. 2000; Panzarasa et al. 2002; Thomas-Hunt et al. 2003; Deffuant 2001). These components can come together in different ways to produce varied dynamics and outcomes, but some common patterns have been described in the literature.

1.4 Kerr and Tindale (2004) illuminate some of these patterns in their overview of the literature on collective decision making processes and outcomes. A persistent finding is that in group discussions, agents more highly weigh the input of group members with similar positions on an issue than the input of members whose positions differ (Kameda et al. 2002; Tindale and Kameda 2000). In contrast, the prototypical model described in Watkins et al. (2013) sets up respect independent of the similarity of positions to allow for greater flexibility in representing a situation where, for example, an agent may support someone else's differing position if they trust the other's expertise more than their own.

1.5 Additionally, collective decision-making may be structured such that multiple actors have input, but only one or a few actors have ultimate decision-making power. In these cases, the ultimate decision makers can be influenced by people that are seen as highly knowledgeable and respectable (Baumann and Bonner 2004; Ohtsubo & Masuchi 2004; See 2009), by those who have been correct in the past (Budescu et al. 2003), and especially by those who share their positions. Nonetheless, these decision-makers still tend to weigh their own preference the most (Harvey et al. 2000; Yaniv & Kleinberger 2000).

Agent-based modeling of collective processes

1.6 Given the multiple components of collective decision-making, the dynamic interactions between these components, and the group-level properties that emerge from these interactions, it is useful to view groups involved in addressing conflict and reaching consensus as complex adaptive systems (Arrow et al. 2000). Agent-based modeling has long been used to study these systems. Agent-based models that test hypotheses about specific interaction mechanisms tend to be purely theoretical. For example, Mungovan et al. (2011) investigate how random interactions and decision heuristics impact the evolution of norms in social networks. They find that norm convergence is facilitated by more frequent and more heavily weighted random interactions, particularly when the decision is binary. The authors argue that this is a result of having more information passed between agents. Franks et al. (2013) use what they call, "influencer agents" to promote group convergence on convention (norm) acceptance. These agents are influential because, although they have equal authority as the other agents, they promote their own convention but ignore most of those being shared by the other agents. The authors show that just a few influencer agents can be beneficial, and promote quality conventions, but they can also be detrimental if the agent is "malicious or faulty" and chooses to promote low-quality conventions. The work by Franks et al. (2013) as well as Garlick and Chli (2009) suggest that communication is key to an agent's influence (in that, without it, their influence is reduced). These studies also parallel work on the diffusion of innovations, which is akin to collective decision-making in its exploration of the processes by which ideas are adopted and spread through communities. In addition to other factors, the diffusion of innovations literature highlights the ways in which respected agents, or opinion leaders, facilitate the spread of innovations and the importance of the social accessibility of these key agents (Rogers 1995).

1.7 The prototypical model in Watkins et al. (2013) confirms these findings, and adds insights as to how decision convergence in an ecological restoration organization is delayed with growing size and number of subgroups, and with the influx of external information. This model also shows that more complex behaviors, like entrenchment and cost of dissent, tend to create greater variety in process outcomes.

Integrated empirical data analysis and agent-based modeling

1.8 In addition to contributing to theory through the explicit formulation of interaction mechanisms in collectives, agent-based models are also flexible enough to capture the effects of specific agents and/or groups of agents, and their particular characteristics on the structure of the decision making process (Brown et al. 2008). Therefore, the value of agent-based modeling is expanded when integrated with empirical data. Many scholars have argued that empirical data should be an essential component of agent-based modeling, to inform the micro-level processes and the macro-level outputs of the models, and to test and validate them (Boero & Squazzoni 2005; Robinson et al. 2007). Empirical data can include one or, ideally, a combination of the following: surveys or questionnaires, field and lab experiments, companion modeling, GIS and other spatial data, and, most importantly for our work here, ethnographic methods (interviews and participant observation) (Janssen & Ostrom 2006; Robinson et al. 2007; Brown et al. 2008; Smajgl et al. 2011).

1.9 Ethnography is increasingly being recognized as a useful tool for informing agent-based models (Agar 2004a, 2004b; Yang & Gilbert 2008). An ethnographic approach aims to illuminate the causal connections and interactions between the elements in a human system (Agar 2004b). In the context of collective decision-making, researchers can use ethnographic data to identify (i) key agents, their positions, and their

relationships with, and influence on, other actors, (ii) the step-by-step processes of actions and interactions among actors, (iii) explanations for when and how often these processes occur, and (iv) a broad understanding of the history and nuances of interactions, group processes, and the decisions that have emerged from these structures (Robinson et al. 2007; Yang & Gilbert 2008). This information directly maps into the conceptual description of an agent-based model of particular case studies. In this manner, ethnographic research and agent-based modeling can be viewed as complementary steps towards advancing theory. The theoretical framework guides both preliminary modeling and data collection and analysis, which reflect and inform each other, allowing us to formulate and test different hypotheses.

1.10 The process of using ethnographic data to inform ABMs necessarily requires the researcher to translate such data into numbers and if-then rules. Agar (2003, 2004a, 2004b, 2005) has written about the importance of using qualitative data to inform models, and the challenges it poses. He describes the translation process as going through a series of questions in which the researcher articulates the details of behavior and changes in that behavior. These moments of change can be thought of as thresholds, and can be relative approximations. Rather than finding numbers that have strict meanings based on the ethnographic data, Agar argues that the goals should be to select numeric values that reflect real differences in the world the ethnographer has observed and " … correspond to a difference that makes a difference in the kind of world being modeled" (Agar 2003, paragraph 4.12). Since a model is not meant to reflect the nuances of what a change in behavior *feels* like or *means* for a person, but rather to replicate the process and result of behavior change, using thresholds that are valid in a "more or less" sense is appropriate:

> "Models can't represent an ethnographic account in a virtual reality... What models can do is clarify an idea, one that a researcher has concluded is central and key in understanding a particular phenomenon, an idea that is 'post-ethnographic.' An agent-based model can't do the ethnography. It can't represent it, either. What it can do is test a critical piece of the structure/agency puzzle after you're done." (Agar 2003, paragraph 5.12)

Thus, qualitative analysis can reveal not only patterns, but constraints on those patterns, both of which can be translated into model parameters.

1.11 Most of the literature on ethnographically informed agent-based models focus on land-use and natural resource management. Huigen (2004, 2006) explored the effects of cultural and economic motivations on land-use decisions in the Philippines, and Bharwani et al. (2005) modeled how agents in South Africa cope with food scarcity due to climate change. These studies and others (e.g. Berman et al. 2004; Terán et al. 2007; Manson & Evans 2008; Boone et al. 2011; Chion et al. 2011) involve collective decision-making processes, but they tend to focus on collectives that are either smaller (e.g. households) or larger (e.g. community) than in this study, and that operate over extended periods of time (i.e. years). Further, greater consideration is given to the influence of external factors (e.g., social, environmental) on individual decision outcomes, rather than on how factors influence inter-agent interaction.

1.12 Few studies use ethnographic data to inform models of collective decision-making related to a single decision. Altaweel et al. (2010) present a model in which rural Alaskan villagers' pass (or do not pass) laws granting access to potable water, informed by field observations. Deffuant (2001) also provide a successful example of integrating ethnographic data and agent-based models to understand how interactions between individual farmers lead to group dynamics related to opinion change and diffusion of innovation. Our study seeks to contribute to this literature by expanding on a stylized model of collective management of urban ecological restoration (Watkins et al. 2013) with case-specific ethnographic data, seeking to develop explanations for these cases and generalizable insights for other cases. We used the stylized model as a template to organize the empirical data on organizational structures, inter-agent interactions within this structure, agents' position about particular ecological restoration options, and their respect for each other. We used the empirical data to adapt the model mechanisms and select appropriate parameter values for the stylized model. Simulated outputs were contrasted with observations, and discrepancies were resolved with meaningful adjustments of parameter values, i.e. with reasonable quantitative representation of the qualitative data. This exercise of alignment allowed us to identify relevant hypothetical scenarios to test with our empirically informed model. Our analysis focuses on how model mechanisms and parameters function together to explain the distribution of agents' position throughout the collective decision-making process, and how quickly positions converge.

🌍 Methods

Selection of cases and parameterization

2.1 The prototypical model developed in Watkins et al. (2013) was informed and parameterized with an iterative process of literature review, *a priori* knowledge, and preliminary ethnographic data concerning collective decision-making processes found in member organizations of the Chicago Wilderness consortium. The literature review identified status (respect), the introduction of new information, and a variety of decision strategies as important factors in the collective decision making process. To supplement these concepts, we conducted over sixty in-depth semi-structured interviews with decision makers holding different positions and with varying authority in ten organizations within Chicago Wilderness. We also observed dozens of organization meetings and restoration workdays. Interviews were transcribed and broad thematic codes were created (Bernard 2005; Glaser & Strauss 1967) using NVivo (2012), a qualitative data analysis software. Subsets of the data were jointly coded to develop initial categories of organizational structure and interaction styles, and to ensure validity and shared understanding. The data was further split among researchers with relevant expertise (e.g., anthropology, sociology) and continued to be coded. Our qualitative observations and analysis confirmed the relevance of the factors identified in the literature (respect, new information, and variety in decision strategies), and revealed the importance of two additional factors and mechanisms: organization structure, and the types and frequency of participant interactions within and between groups. Detailed and data-rich explanations of these mechanisms can be found in Watkins et al. (2013).

2.2 Model development forced us to be explicit about key agents and their characteristics, and about the sequence of interaction mechanisms among all agents. Using the prototypical model as one of the guiding frameworks, two of the authors (Watkins and Westphal) analyzed case interviews and the thematic codes and found relevant data regarding decision making, gaining important insights into individuals' position, personality, and relationships with each other. Following standard practice in agent-based modeling (Railsback & Grimm 2012), we used the qualitative data to establish initial categorical distinctions among agents relative to their positions and mutual respect (e.g., 0.2, 0.5 and 0.9 for low, medium, and high values, respectively), and about their frequency of interactions within a generalized organizational structure (e.g., 25%, 50%, and 75% for low, medium, and high frequency, respectively). This initial parameterization allowed us to explore interaction effects as we fine-tuned parameter values to match the cases selected, and to generate hypotheses about the effects of structural and behavioral changes.

2.3 As an illustration, we include here an example of how we derived position and respect values between two agents from qualitative data.

> YJ: "A lot of it revolves around when and when not to burn. I push the envelope and say, 'You know, it's October, it's early, but I betcha something could go today, if we really tried.' You know, these guys got instilled about these western fires, and Safe, safe, safe, safe! And it's like, you know, it's too entrenched."
> LB3: "YJ has been an advocate of burning more than anyone. And sometimes, if you asked him, he might say that we're a hindrance… We haven't hindered anything … YJ would say, 'Hey, it's supposed to rain today. Let's give it a shot.' And we'd be looking at it as, 'Boy, we're overloaded already. We have to get other things done.' That sounds like we're not into burning. My guys are into burning big time. They love burning. That's what they've all done for years. It's not that—it's just me saying I'm not going to send out a crew of 10 guys when the rain is showing on the radar. But he'll look at it as: We have to take a chance."

From these data, we could differentiate LB3's more reserved position on when to burn as compared to YJ's position that allowed more risk. Similarly, the tone with which the two agents spoke of the other—a restrained frustration, perhaps—cued us in on lower respect levels, as compared to agents where that tone was absent when talking about fellow colleagues.

2.4 With respect to interactions, formal meetings are fairly straightforward (all agents interact at regular intervals), but informal interactions required translation of qualitative data. To illustrate:

> EI: "We try to keep it every 2 weeks … a [restoration technician] and an [ecologist] staff meeting … we discuss either ongoing issues, or updates on projects, or coordination of work to make sure we're not crossing each other's … you know, going at cross purposes, working out conflicting issues and interests, those types of things … we try. We try. I think we schedule it every two weeks, but we'll probably get 15 in a year. 12 maybe in a year."
> This data corresponds to a formal intergroup meeting once a month, as described for case 1, below.

2.5 Conversely, for case 2, ZC describes a lack of communication, both formally or informally:

> ZC: "You know, that's the thing. I don't fully know. Because a lot of that, it's like, some of the stuff, there's no like team or group meeting keeping everyone informed of what's going on. Sometimes they call up MC and he handles it directly and it's some outside group that's kind of handling it, like RI4, and we don't get records or information on what the heck actually happened out there, or what the story is. So how do you track it? Sometimes you hear about it, "Oh yea, we did this" and you hear about it later in the season or something. So it's a little tough to incorporate into burn plans and monitoring plans, if you're not informed."

From this excerpt we derived relatively low levels of interaction across the subgroups. Together, these quotes are illustrative of the range of interaction frequencies that we uncovered in the interviews and that were used to guide decisions about parameter values for those interactions.

2.6 The cases modeled here were chosen based on the availability of detailed data on particularly contentious collective decision-making processes; our aim was to provide explanations for conflict and suggestions to facilitate consensus building. For each case, we crafted a unique story from multiple respondents about a particular restoration decision-making process (including data on inter-agent relationships and interactions), which constituted the basis for model adaptation and calibration (described below). The cases describe a decision process that happens seasonally (case 1, prescribed fire) or occurs throughout the year (case 2, seeding).

Case 1: Prescribed fire

2.7 In the prescribed fire case, there are two subgroups within an organization, ecologists and restoration technicians, who must work together to decide when and where to conduct prescribed fires at natural area sites undergoing ecological restoration. They must do so within the burn season, which is approximately six weeks long (30 workdays) and is characterized by optimal ecological burn conditions. Given optimal conditions, all agents involved in the case would prefer to burn as many acres as possible. However, levels of perception of risk vary among these actors. The use of prescribed fires, particularly in urban areas, is constrained by the surrounding urban matrix as well as the occurrence of optimal weather conditions. Among other potential problems, the spread of smoke to houses, schools, and freeways represents potential health and visibility risks and must be avoided. Substantial effort goes into preparing for and conducting a prescribed fire, and retracting a decision on the day of a burn is highly undesirable.

2.8 The ecologist subgroup has a strong desire to burn in order to achieve the restoration outcome at a given site, and they are more risk-bearing. The restoration technician subgroup also has a strong desire to achieve particular ecological outcomes, but as the group actually conducting the burn and directly responsible for its outcome, they are more risk-averse. This difference in position (that is, their opinion) about when to burn is accompanied by the lower levels of respect that some members have for each other. These differences have led to conflict between agents and an inability to agree about whether or not to burn on any given day. In response to these disagreements, the organization hired a staff member to act as a liaison between the two subgroups (an agent we call KL). Although KL is based in the ecologist's subgroup, s/he is well respected by all, respects all, and interacts frequently with agents in both groups. The mutual respect and frequent interactions led to less friction and faster convergence, as evidenced in our ethnographic data by descriptions of increased cooperation.

Case 2: Seeding native plants

2.9 In this case, there are four subgroups (ecologists, restoration technicians, volunteer management personnel, and volunteer restorationists), who must decide when to sow native seed after a natural area has been cleared of invasive plants. The practice of seed collection and dispersal of certain plant species is common, but the specifics of where and when it should take place, and how much of which species should be distributed, can be contentious.

2.10 Ecologists and restoration technicians prefer to delay adding native seed stock to the site after clearing invasive brush or after a burn, while volunteer management personnel and volunteer restorationists prefer to distribute seed immediately after clearing or burning has occurred. Moreover, inter-group respect is low between the volunteer-related subgroups (management personnel and the volunteers) and the technical subgroups (restoration technicians and ecologists). Ethnographic data suggests that the subgroups struggle to reach a consensus on how long to wait to sow after clearing. The organization has made several unsuccessful attempts to hire a liaison to facilitate communication among subgroups. Further, protracted disagreements about a variety of other restoration actions and a history of struggle over power sharing plague this organization and contribute to persistent low respect among groups. Currently, the outcome being enacted is close to the volunteer restorationist subgroup position.

2.11 All of the authors discussed the cases as they were informed by the modeling framework of Watkins et al. (2013). From these analytical conversations, we created a template that guided the representation of organizational and interactional structure (Figure 1). This template allowed us to organize the qualitative data and derive values for positions, respect, interaction types and frequencies, and outcomes of interest for each.
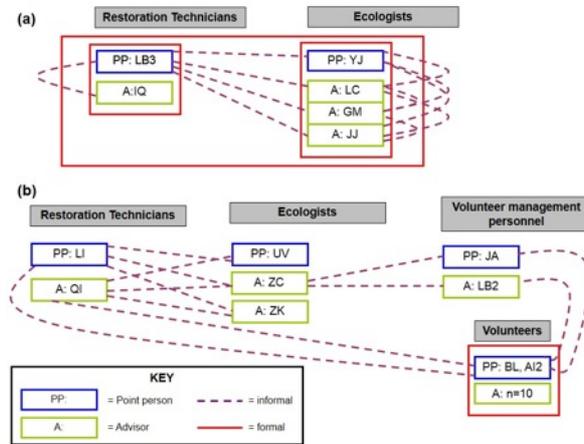

Figure 1. Ethnographic data templates for the baseline scenario of: a) Case 1, Prescribed fire; b) Case 2, Seeding native plants. Note: acronyms stand for pseudonym initials given to each agent.

Model development

2.12 To avoid overlap with Watkins et al. (2013), we provide a broad description of the model components and procedures, and give more detail on the modifications introduced to adapt and calibrate the model to the decision-making processes described in the cases above. The model code can be found in https://www.openabm.org/model/4065/version/1/view.

Agents

2.13 While in the prototypical model (Watkins et al. 2013) the number of agents was fixed and evenly distributed across groups, empirical data was used to create agents that correspond with actual members of subgroups in each case. Each subgroup has a group leader, referred to as the point person who meets with point persons in other subgroups at regular intervals (Figure 1). All other agents are referred to as advisors.

2.14 Unlike the random assignment of respect and position values used in the prototypical model, agents are given a position about the particular restoration decision based on ethnographic data. For Case 1 (prescribed fire), a position of 0 represents the perception of no risk for burning (and thus a position to burn), while a position of 1 represents the perception of very high risk (and the position to not burn). For Case 2 (seeding), 0 represents the position to immediately seed after clearing of invasive species, while 1 represents the position to significantly delay seeding. Agents also are assigned constant respect values between 0 and 1 for the position of all other agents and a value of 1 for their own position, based on interview data. Respect is limited to the decision at hand only, and does not represent general self-confidence or likeability of others. Respect can, however, be influenced by past experiences between agents concerning restoration actions, and thus feed into the respect values assigned to each agent at the beginning of a run.

Events in a run

2.15 Appendix A contains a description of the full schedule of events within a run. We focus here on describing the interactions and updating of positions that are at the core of the collective decision-making process.

2.16 Each time step in the simulation is one workday. There are four types of interactions that may occur in each time step, defined by the agents involved and their frequency and or daily likelihood of occurrence: (1) formal intergroup interactions at regular intervals involving the point persons of each subgroup; (2) formal intra-group interactions occurring at regular intervals and involving all the advisors and the point person from a single group; (3) informal inter-group interactions involving a specific pairing of agents from two different subgroups, with each pairing assigned a daily probability of meeting, and (4) informal intra-group interactions involving at least two agents in the same group; the meeting occurs at a specified daily probability (a maximum of 1 meeting per day), and the agents involved are selected according to individual probabilities. The informal interactions (3) and (4) required the most significant departure from our prototypical model, whereby we needed to better reflect the interaction mechanisms in the two selected cases. While in the stylized model all agents are equally likely to participate in informal meetings, organizing the ethnographic data according to Figure 1 showed that specific pairs of agents across groups interacted at unique frequencies, while agents within groups had different levels of involvement in spontaneous meetings, and the groups themselves showed different levels of internal activity.

2.17 As agents interact during the simulation, their positions change based on the level of respect agents have for each other's position. To compute this change, respect values among the agents involved in a specific interaction are first normalized to add up to 1 (Watkins et al. 2013). Each agent's position value is then updated by calculating the average of the positions of all interacting agents, weighted by the normalized respect that each agent has for each other, as follows:

$$ p_{i,t+1} = \sum_{j=1}^{n} r_{ij} \times p_{j,t} \qquad (1) $$

where:
$p_{i,\,t+1}$ = updated position of agent i;
n = total number of agents involved in a specific interaction;
$r_{i,\,j}$ = respect that agent i has for agent j (including itself), normalized among the n interacting agents;
$p_{j,\,t}$ = current position of agent j;

If all of the position values are within 0.01 of each other, consensus is assumed and the run stops. At that time, the length of the run is recorded as a measure of time and effort to reach consensus. Individual and collective position (the average of all individual positions) is saved at each time step to track how it changed from the initial positions. We use these output measures to see to what extent they parallel our ethnographic data.

Calibration and sensitivity

2.18 Once we had a running version with all the components and values for each case, we found that initial parameter values resulted in faster convergence than empirical observations. We conducted systematic adjustments of each of the parameters (position and respect values, and interaction rates) to obtain model outcomes (length of run and final collective position) that reasonably reflected the observations for the baseline scenarios (Case 1, scenarios a and b, and Case 2, scenario a, described in detail below). Interaction probabilities are more easily derived from the empirical data (e.g. two specific agents interact roughly once per week, making their likelihood of interaction at each time step 20%), and thus easier to adjust. Conversely, respect and position are more difficult to represent as numbers from the interview data, and required greater attention during calibration. The biggest adjustment we made was to represent an extremely low respect value as 0.01 rather than 0.1 or 0.2. While the latter are low values, over the course of a run many interactions occur, and positions would still converge faster than observed. Only when the value approached 0.01 was a low-respected agent less able to influence the process in a manner that matched observations. Once these were set, sensitivity tests showed that the outcomes were robust to ±5% changes in the value of all parameters (Railsback & Grimm 2012).

2.19 Model calibration and sensitivity tests allowed us to identify key mechanisms (e.g., interaction frequency), structures (e.g., group size), and agent characteristics (e.g., respect values) that seemed to most influence the convergence of the collective, and thus prompted us to construct hypothetical scenarios to address specific questions about the effect of plausible behavioral and organizational changes on the outcomes. Below we describe the settings and results of the baseline (i.e., empirical) case and the hypothetical simulation experiments for each case.

🌐 Simulation experiments

3.1   In this section, we describe the baseline (i.e., empirical) setting for each case, informed with ethnographic data, followed by hypothetical scenarios with their corresponding parameter changes to reflect our hypotheses and questions about the influence of specific agents and of organizational structure and function on the outcomes. Each scenario was run 20 times, and results were averaged across the 20 runs.

Case 1: Prescribed fire

Empirical scenarios

3.2   *Scenario 1a.* In this organization, the agents hold the others in their own subgroup in high regard, interact with them frequently and either have the same or similar starting positions, so the entire run time is spent getting the two groups' positions to converge. The initial position, respect values and interaction pairing and rates are set to represent these relationships (Tables 1 and 2). All groups have a monthly formal interaction (once every 20 days in a simulation). The ecologist subgroup has one intragroup formal meeting every 3 months, while the restoration technician subgroup has a daily formal meeting.

3.3   Running this baseline scenario results in an average length of time to reach consensus about a decision was 40.2 days (Table 3). This is longer than the optimal burn season (30 workdays), which is in line with the empirical data. Consensus is delayed because agent LB3 (in the restoration technician subgroup) is the only intermediary between the two subgroups and does not have high respect for the agents in the ecologist subgroup. Furthermore, the low respect is reciprocated—the agents in the ecologist subgroup have low respect for LB3. Collective position does not change over the course of a run (Figure 2a).

Table 1. Position value of each row agent and respect values of each row agent for each column agent for scenarios 1a (no KL) and 1b (with KL). Blank cells indicate that the agent pairs never interact (and thus do not influence each other).

	SUBGROUP Ecologists					SUBGROUP Restoration technicians		
	YJ	LC	GM	JJ	KL	LB3	IQ	Position
YJ	1	0.9	0.9	0.9	0.9	0.01		0.2
LC	0.9	1	0.9	0.9	0.9	0.2		0.4
GM	0.9	0.9	1	0.9	0.9	0.2		0.4
JJ	0.9	0.9	0.9	1	0.9	0.2		0.4
KL	0.9	0.9	0.9	0.9	1	0.9		0.5
LB3	0.01	0.2	0.2	0.2	0.9	1	0.9	0.8
IQ						0.9	1	0.8

Table 2. Probabilities of informal interactions for scenarios 1a (no KL) and 1b (KL): a) in daily intergroup meetings between each row agent and each column agent; b) in daily intragroup meetings.

(a) Intergroup informal

		SUBGROUP Restoration technicians	
		LB3	IQ
SUBGROUP Ecologists	YJ	50%	0%
	LC	25%	0%
	GM	25%	0%
	JJ	25%	0%
	KL	75%	0%

(b) Intragroup informal

SUBGROUP Ecologists 1 meeting per day	
YJ	100%
LC	25%
GM	25%
JJ	25%
KL	75%

SUBGROUP Restoration technicians 1 meeting per day	
LB3	100%
IQ	100%

Table 3: Case 1 scenario outputs, averaged over 20 runs.

Scenario	Length of Run	SD	Collective Position	SD
1a - No KL – baseline	40.2	5.671	0.50	0.000
1b - With KL - high respect and high interactions	14.9	5.326	0.50	0.000
1c - With KL - high respect and low interactions	26.7	5.017	0.50	0.000
1d- With KL - low respect and high interactions	31.8	4.720	0.49	0.002

3.4   *Scenario 1b.* The frequency and type of interactions and levels of respect are the same as in scenario 1a, except for the addition of KL, who is highly respected by all other agents, reciprocates that respect, and interacts at a higher rate than all other agents (Tables 1 and 2). In this scenario, all of the agents' positions converge in an average of 14.9 days, well within the 30-day burn period, but there is no impact on the collective position over time (Figure 2b). The rapid convergence reflects the intended changes in this organization that the collective hoped for in bringing in KL, as documented in our interviews.

Hypothetical scenarios

3.5   We included two additional scenarios to further examine the effect of KL's involvement in the process, seeking to distinguish the influence of reciprocal high respect from that of frequency of interactions.

3.6   *Scenario 1c.* This scenario replicates 1b, except that KL interacts infrequently in informal interactions both within and across groups. Positions converge more quickly than in scenario 1a, (26.7 days), but slower than in scenario 1b. Again, there is no change in collective preference during the simulations (Figure 2c).
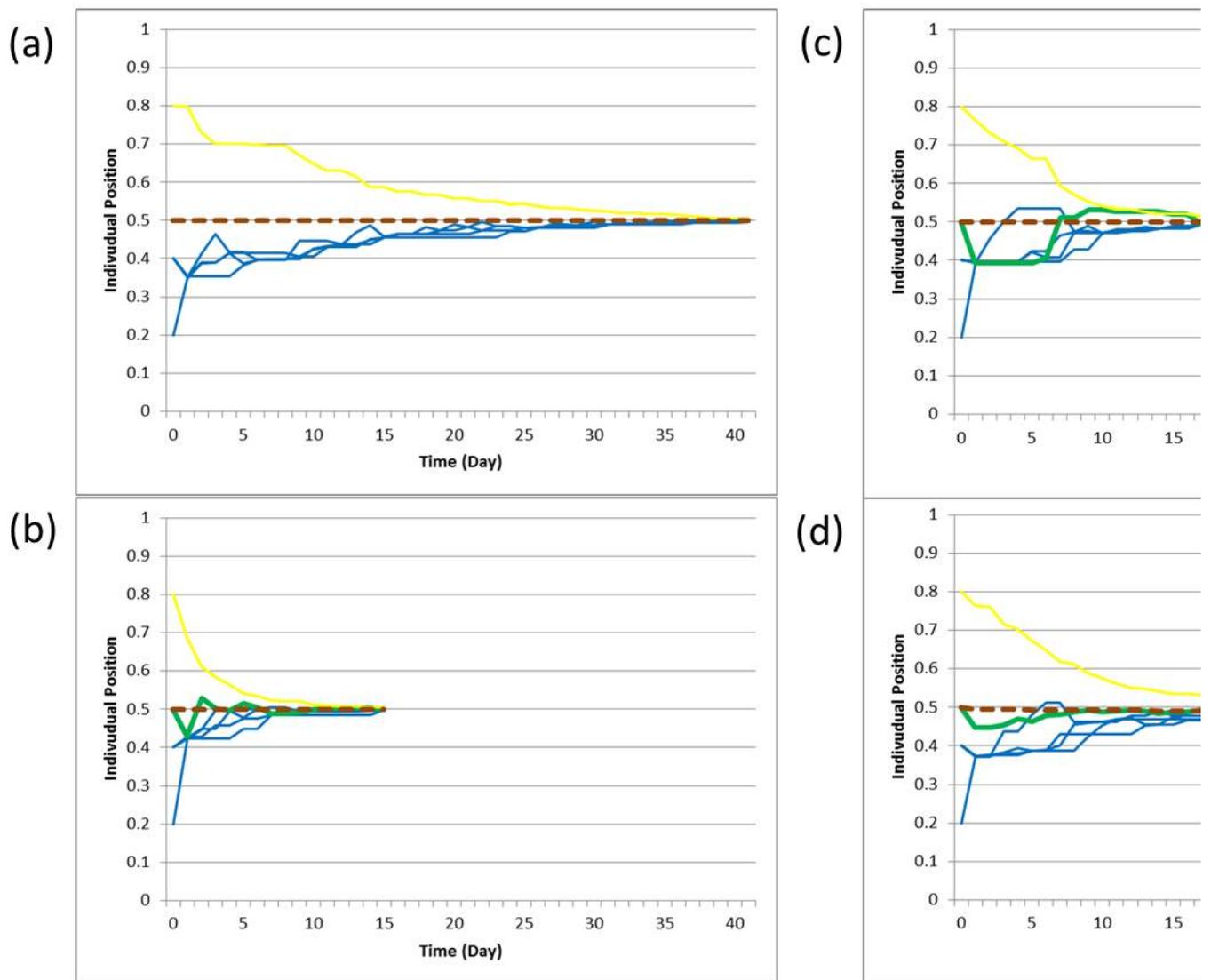
Figure 2. Sample runs for Case 1 empirical (a and b) and hypothetical (c and d) scenarios. Individual positions of ecologists are shown in blue, of restoration technicians in yellow, and of KL in green. [

3.7 *Scenario 1d*. This scenario replicates 1b, except that respect between KL and all other agents is mutually low (0.1). Convergence is quicker than in scenario 1a (without KL), but it is slower than 1b or 1c (31.8 with a SD of 4.407). This means that there is rarely a decision made by the end of the 30-day burn period. Collective position does not change during a run (Figure 2d).

3.8 In sum, both respect and frequency of interactions reinforce each other to push the process towards faster convergence, even if the ultimate collective position outcome does not vary. In other words, the variance in individual positions is greatly reduced around an average value that is similar to the average value at the beginning of the run.

Case 2: Seeding native plants

Empirical scenario

3.9 *Scenario 2a*. In this case respect levels between pairs of agents is unequal. The agents in the volunteer restorationists subgroup have high respect for the agents in the restoration technician subgroup. This is because the restoration technicians agents do not have particularly strong opinions about seeding, and the volunteers' primary relationship to the restoration technicians is requesting contract work and other non-seed related special actions (e.g. tree removal), for which the restoration technicians have garnered high respect from the volunteers. Conversely, both the ecologists and the volunteer restorationists are outspoken

and adamant about their positions on seeding, which differ drastically. As a result, agents in the restoration technician subgroup feel pressure from the agents in the ecologist subgroup to "side" with their fellow staff members, rather than collaborate with volunteers. Overall, and perhaps because of these tensions, there are fewer opportunities to interact. We represented these tensions in the chosen parameter values for initial position and respect values (Table 4), and interaction rates (Tables 5). There are no intergroup formal interactions in this case. The volunteer restorationist subgroup has an intragroup formal meeting every 6 weeks (once every 30 days in a simulation), while the ecologists, restoration technicians, and volunteer management personnel do not have any intragroup formal interactions.

3.10   The average length of a run (time to convergence) was 172.9 days (Table 6), in line with empirical data. The limited interactions between subgroups, infrequent informal interactions within the volunteer restorationist subgroup, and low respect for agents outside one's own group are the reasons why it takes months to reach a consensus. Collective position does change slightly over the course of a run, ending on average at 0.326 (Figure 3a). The collective position shifts away from the initial value because of the non-reciprocal nature of the relationship between the two agents in the restoration technician subgroup (QI and LI), who respect the point persons in the volunteer restoration subgroup (AI2 and BL) less than AI2 and BL respect QI and LI in return. The restoration technicians are intermediaries between the volunteer restorationists and the ecologists. With the lowered respect for volunteers, the restoration technicians are more in line with the ecologist's respect for volunteers. The ecologist subgroup is thus able to slightly influence the collective position towards their own subgroup's initial value (Figure 3a). Nonetheless, the overwhelming number of volunteer restorationists maintains the final collective position close to their own group's initial position.

Table 4. Position value of each row agent and respect values of each row agent for each column agent for scenarios 2a (no KL) and 2b (KL). Blank cells indicate that the agent pairs never interact (and thus do not influence each other).

	SUBGROUP Ecologists				SUBGROUP Restoration technicians		SUBGROUP Volunteer management personnel		SUBGROUP Volunteer restorationists												
	UV	ZC	ZK	KL	QI	LI	JA	LB2	AI2	BL	OR	V2	V3	V4	V5	V6	V7	V8	V9	V10	P
UV	1	0.9	0.9	0.9	0.2	0.5															0.9
ZC	0.9	1	0.9	0.9	0.2	0.5															0.6
ZK	0.9	0.9	1	0.9	0.2	0.5															0.9
KL	0.9	0.9	0.9	1	0.9	0.9	0.9	0.9	0.9	0.9											0.5
QI	0.2	0.2	0.2	0.9	1	0.9	0.2	0.2	0.2	0.2											0.5
LI	0.5	0.5	0.5	0.9	0.9	1	0.5	0.5	0.5	0.5											0.3
JA				0.9	0.2	0.5	1	0.9	0.9	0.9											0.2
LB2				0.9	0.2	0.5	0.9	1	0.9	0.9											0.2
AI2				0.9	0.9	0.9	0.9	0.9	1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.1
BL				0.9	0.9	0.9	0.9	0.9	0.9	1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.1
OR									0.9	0.9	1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.1
V2									0.9	0.9	0.9	1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.1
V3									0.9	0.9	0.9	0.9	1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.1
V4									0.9	0.9	0.9	0.9	0.9	1	0.9	0.9	0.9	0.9	0.9	0.9	0.1
V5									0.9	0.9	0.9	0.9	0.9	0.9	1	0.9	0.9	0.9	0.9	0.9	0.1
V6									0.9	0.9	0.9	0.9	0.9	0.9	0.9	1	0.9	0.9	0.9	0.9	0.1
V7									0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1	0.9	0.9	0.9	0.1
V8									0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1	0.9	0.9	0.1
V9									0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1	0.9	0.1
V10									0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1	0.1

Table 5. Probabilities of informal interactions for scenarios 2a (no KL) and 2b (KL): a) in daily intergroup meetings between each row agent and each column agent; b) in intragroup meetings at the specified frequency.

	SUBGROUP Ecologists				SUBGROUP Restoration technicians		SUBGROUP Volunteer management personnel		SUBGROUP Volunteer restorationists	
	UV	ZC	ZK	KL	QI	LI	JA	LB2	AI2	BL
UV	--	--	--	--	10%	10%	0%	0%	0%	0%
ZC	--	--	--	--	20%	20%	5%	5%	0%	0%
ZK	--	--	--	--	10%	10%	0%	0%	0%	0%
KL	--	--	--	--	50%	50%	50%	50%	0%	0%
QI	0%	0%	0%	0%	--	--	0%	0%	10%	0%
LI	0%	0%	0%	0%	--	--	0%	0%	0%	10%
JA	0%	0%	0%	0%	0%	0%	--	--	10%	10%
LB2	0%	0%	0%	0%	0%	0%	--	--	10%	10%
AI2	0%	0%	0%	0%	0%	0%	0%	0%	--	--
BL	0%	0%	0%	0%	0%	0%	0%	0%	--	--

(a) Intergroup informal

SUBGROUP	
Ecologists	
1 meeting every other day	
UV	100%
ZC	50%
ZK	20%
KL	75%

SUBGROUP	
Restoration technicians	
1 meeting per day	
QI	100%
LI	100%

SUBGROUP	
Volunteer management personnel	
1 meeting per day	
JA	100%
LB2	100%

SUBGROUP	
Volunteers	
1 meeting per day	
AI2	100%
BL	100%
OR	30%
V2	10%
V3	10%
V4	10%
V5	10%
V6	10%
V7	10%
V8	10%
V9	10%
V10	10%

(b) Intragroup informal

Table 6: Case 2 scenario outputs, averaged over 20 runs.

| Scenario	Length of Run	SD	Collective Position	SD
2a - No KL – baseline	172.9	13.570	0.326	0.006
2b - With KL - high respect and high interactions	67.5	6.194	0.283	0.006
2c - With KL - high respect and high interactions - exception: KL has low respect for Subgroup Vr agents	112.1	10.002	0.591	0.026
2d - With KL - high respect and high interactions - Subgroup E and Vr same size	201.4	31.638	0.446	0.000
2e - No KL - Subgroup D point person replaced with agent that interacts more and has higher respect	46.7	7.862	0.255	0.007
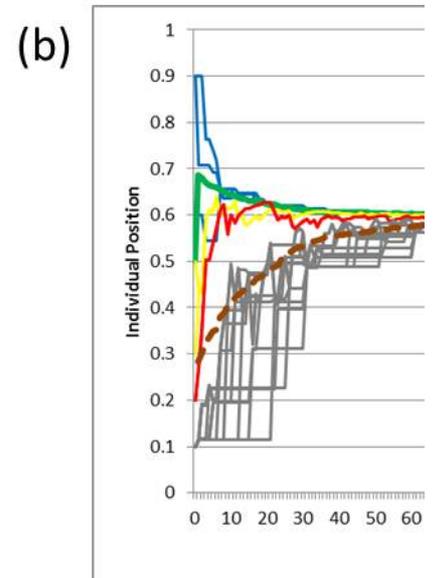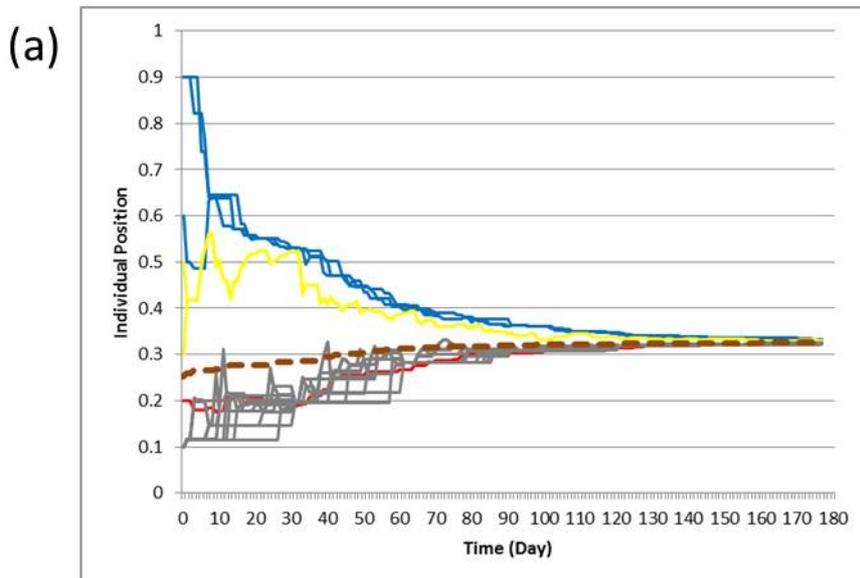
Figure 3. Sample runs for Case 2 empirical (a) and hypothetical (c) scenarios. Individual positions of ecologists are shown in blue, of restoration technicians in yellow, of volunteer management in red, of volunteer restora
dashed brown.

Hypothetical scenarios

3.11　With the understanding of how the tension in Case 2 can hamper collective decision-making, we sought to examine how a mediator like Case 1's KL could support consensus building within Case 2's organizational and relationship structures. We measured the influence of such a KL-type agent on both length of run and final collective position.

3.12　*Scenario 2b.* In this scenario we tested the hypothetical addition of a KL-type agent to the group. The pattern of higher interaction frequencies and higher levels of respect (relative to other agents) simulated in scenario 1a (Tables 1 and 2) are replicated in Case 2 (Tables 4 and 5). As in Case 1, KL is situated in the ecologist subgroup and has a 75% chance of participating in intra-group informal meetings. KL also has a 50% daily probability of informally interacting individually with all members of the restoration technician subgroup, the volunteer management personnel subgroup, and the point persons in the volunteer restorationist subgroup. There are more agents in Case 2 for KL to interact with, so a 50% probability (rather than 75% probability, like in Case 1) allows KL to meet more frequently but not an unrealistic amount. As expected, with KL, the average convergence time drastically drops to 67.5 days. Collective position changes but since runs are much shorter, the ending value is lower at 0.28 on average, still closer to the volunteer restorationist subgroup's position. The shorter runs reduce the total number of interactions that take place, which are thus not enough to change the position of the greater number of agents in this subgroup.

3.13　*Scenario 2c.* This hypothetical scenario replicates 2b except that KL has low respect (0.01) for the volunteer restorationists. The purpose of this scenario was to see if changing KL's respect scores could bring the collective position closer to the average of the ecologist subgroup's. The runs took longer than 2b but were still shorter than the baseline and the final collective position was shifted to 0.59 on average, bringing it closer to the positions of the ecologists as a result of this asymmetrical respect from KL (Figure 3b).

3.14　*Scenario 2d.* We hypothesized that the reason the collective position was closer to the positions of the volunteer restorationists was that there are more agents in this group than there are in the other groups. Thus, scenario 2d tests the impact on collective position of equalizing the number of agents in the ecologist and volunteer management subgroups. In addition to having KL, 8 new agents are added to the ecologists subgroup, for a total of 12. Respect, position, and interaction values are the same as scenario 2b. Following the position values of their fellow subgroup members, additional ecologist subgroup agents have positions of 0.9, respect values for their own positions of 1, and respect values for the agents in their own group of 0.9. The additional agents only interact with agents in their own group, and they do so with the same probability that the advisors do in the volunteer restorationist subgroup (10%). Runs in this scenario lasted even longer than in the baseline scenario without KL, but this is due to the fact that there are so many new agents who rarely interact with anyone else, delaying convergence. As a result, the final collective position shifted away from the volunteers' position towards the center, averaging 0.45 (Table 6).

3.15　*Scenario 2e.* Recall that the point person in the ecologist subgroup is not highly respected by agents outside of her own subgroup (Table 4). To test the effect of a change in leadership in the ecologist group, we changed the attributes of the ecologist subgroup point person (now called NB) to reflect those of KL. Like KL, NB interacts more frequently with other agents, has high respect for others (0.9), and is highly respected (Table 7). While all other agents respect him more than they did UV (the previous point person), the respect values from agents in the volunteer management personnel subgroup and volunteer restorationist subgroup are slightly lower (Table 7). This reflects a reservation on the part of the volunteers to trust and work with the new point person (as indicated by ethnographic data on views towards potential incoming point persons). Like the previous point person (UV), NB has a 100% probability of participating in intra-group informal interactions. NB now has a 50% chance of having a paired inter-group informal interaction each day with all members of the restoration technician subgroup (as compared to the 10% chance of UV) and also with the volunteer management personnel subgroup. Further, NB now has a 50% chance of having an informal interaction with the point persons of the volunteer restorationist group, which is an interaction that UV never experienced.

Table 7. Section from Table 4, showing the respect and position values of agent in row for agent in column for scenario 2e (with NB). Blank cells indicate that the agent pairs never interact.

	Subgroup Ecologists			Subgroup Restoration technicians		Subgroup Volunteer management personnel		Subgroup Volunteer restorationists			
	NB	ZC	ZK	QI	LI	JA	LB2	AI2	BL	OR	V2
NB	1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9		
ZC	0.9	1	0.9	0.2	0.5	0.01	0.01				
ZK	0.9	0.9	1	0.2	0.5	0.01	0.01				
QI	0.9	0.2	0.2	1	0.9	0.2	0.2	0.2	0.2		
LI	0.9	0.5	0.5	0.9	1	0.5	0.5	0.5	0.5		
JA	0.7	0.01	0.01	0.2	0.5	1	0.9	0.9	0.9		
LB2	0.7	0.01	0.01	0.2	0.5	0.9	1	0.9	0.9		
AI2	0.5			0.9	0.9	0.9	0.9	1	0.9	0.9	0.9
BL	0.5			0.9	0.9	0.9	0.9	0.9	1	0.9	0.9
OR								0.9	0.9	1	0.9
V2								0.9	0.9	0.9	1

3.16　As a result of having a point person who behaves similarly to a liaison, runs on average lasted 46.7 days, the fastest of all scenarios. Collective position, however barely changed over a run, showing that the larger mass of the volunteers' group still drives the final decision (Table 6).

🌐 Implications

Collective decision-making

4.1　The purpose of this study is to advance the theory of collective decision making by integrating two approaches, agent-based modeling and ethnographic research on ecological restoration. We adapted and calibrated a stylized model with empirical data from two cases to identify critical components of the decision process that explain a variety of management styles and corresponding decision outcomes. In Case 1, we show how the addition of a respected liaison who also respects others and interacts frequently facilitates consensus. While each mechanism (high respect and frequent interaction) supports convergence, alone they are not enough to significantly reduce the time it takes to reach consensus. In Case 2, we show how a hypothetical key liaison (with both increased respect and interaction rates) helped to greatly reduce time to reach consensus. Importantly, we also show that making small modifications in values assigned to a point person might lead to similar, if not better, results. As the node connecting the ecologist subgroup to all others, a point person can greatly hamper attainment of consensus, even in the presence of a liaison, by placing obstacles to the flow of information within the organization. Increasing the frequency of interaction and showing high mutual respect can greatly facilitate consensus, especially if by doing so, the point person creates a culture of communication across all members of the subgroups. While we cannot suggest that increasing respect among group members is easy, we can argue that in situations in which diverse and potentially polarizing positions exist and are exacerbated by low respect, *any* agent with increased influence (via interaction frequency and mutual respect) has the potential to promote efficient consensus building processes. However, it is possible that adding a staff person whose main responsibility is acting as a liaison is more feasible than adding this responsibility to an existing staff member's duties.

4.2　In the case where a liaison is biased towards the ecologist subgroup, the power that the volunteer restorationists had via their subgroup size is muted by the lack of respect given to them by KL's group. This pushes the collective position away from that of volunteer restorationists and towards that of ecologists. This result is in line with findings of Franks et al. (2013) that agents can be influential even if they are biased. While a liaison with both reciprocal respect and frequent intra- and inter-group interactions can significantly increase the efficiency of consensus-building, if the goal is to *change* the collective position towards, in this case, a smaller (more conservative) value, a biased key liaison would be necessary.

4.3　Adding group members to the smaller groups to equalize group size increases the length of time to consensus, but the collective position is moved from the baseline values. As more people interact, it takes longer to agree, but there is greater pull towards positions that are farther away from the originally largest group. Given the monetary cost of adding staff as well as extra long deliberation times, this scenario is unlikely to be preferred in the real world. Nevertheless, the implication is that organizational distribution of staff can greatly influence decision outcomes, particularly in relation to where a liaison would be assigned; if new staff were to be hired, their placement within the organization should be carefully considered in relation to desired outcomes.

4.4　Our findings highlight the critical role of influencer agents or opinion leaders and suggest how they might overcome the cognitive biases of individuals who may otherwise hamper the collective decision-making process (Kerr & Tindale 2004; Panzarasa et al. 2002). We also note that the coupling of two relatively simple mechanisms—more frequent interactions and influencer agents—can itself greatly contribute to group consensus. This insight becomes a cautionary note in cases where influencer agents are "faulty," and are able to use their nodal position to steer the collective process towards low quality conventions (Kerr & Tindale 2004; Franks et al. 2013).

Integrating agent-based modeling and ethnographic data analysis

4.5　In this paper, we describe the integration of an agent-based model with ethnographic data of the collective decision making process observed in two organizations conducting ecological restoration. In doing so, we illustrate the usefulness of our prototypical model described in Watkins et al. (2013) in simulating scenario-specific decision processes. Interestingly, analysis of the ethnographic data revealed that, although there is a theoretical basis for representing entrenchment and cost of dissent as was done in the prototypical model (Watkins et al. 2013), only the base model mechanisms were required to reproduce the processes and outcomes of the cases explored here. The simpler mechanisms, albeit with more complicated interaction structures, were sufficient to explain the outcomes. In the process of aligning the model with the data, the model provided a framework for organizing the qualitative data and identifying key agents, their characteristics, and relevant interaction mechanisms and parameter values. The process of model adaptation to the organized data allowed us to explain the cases presented, generate hypotheses about the key agents and interaction mechanisms, and show how key liaisons—particularly those that both interact frequently and have high mutual respect—can be an effective mechanism for facilitating group consensus. In addition to contributing to collective decision-making theory, our work provides case-specific insights as to the inner

workings of our study organizations that can be generalized to other groups engaged in collective decision making. Our integrated approach could be used to explain and explore other cases.

4.6   Decision making in ecological restoration involves uncertainty, lag time, incomplete information, and other issues beyond agents' control (e.g. public perception, weather). DeWulf et al. (2005, p. 15) argue that "environmental management in these [uncertain] conditions implies a shift in attention from solving clearly delineated problems to continuous negotiating and tuning between different actors and expertise domains." Integrating agent-based modeling and ethnographic studies have expanded our understanding of the mechanisms of collective decision making more than either approach alone, allowing us to identify the aspects that organizations do have control over and that can alter the outcomes of their negotiations.

Appendix A: Pseudo-code

1. Initialization
   1.1. Create agents (assignment of values from input files)
      1.1.1. Assign groups
      1.1.2. Assign role as point person or advisor
      1.1.3. Setup position
      1.1.4. Setup respect
   1.2. Setup meeting structures, frequencies and probabilities (assignment of values from input files)

2. Iteration
   2.1. If consensus reached (all positions within 0.01 of each other), end simulation
   2.2. Otherwise, simulate interactions
      2.2.1. If specified interval for intergroup formal meeting reached (all agents in all groups participate)
         2.2.1.1. Normalize respect of all participating agents
         2.2.1.2. Update position of all participating agents (Equation 1)
      2.2.2. Check for occurrence of informal meeting for all groups
         2.2.2.1. Select participating agents (based on probability of participation, Tables 2a and 5a)
         2.2.2.2. If at least two agents selected
            2.2.2.2.1 Normalize respect of all participating agents
            2.2.2.2.2 Update position of all participating agents (Equation 1)
      2.2.3. If specified interval for intragroup formal meeting reached (all agents in each individual group participate)
         2.2.3.1. Normalize respect of all participating agents
         2.2.3.2. Update position of all participating agents (Equation 1)
      2.2.4. If time for intragroup informal meeting (based on frequency of occurrence, Tables 2b and 5b)
         2.2.4.1. Select participating agents (based on probability of participation, Tables 2b and 5b)
         2.2.4.2. If at least two agents selected
            2.2.4.2.1 Normalize respect of all participating agents
            2.2.4.2.2 Update position of all participating agents (Equation 1)

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