Quantifying stakeholder learning in climate change adaptation across multiple relational and participatory networks

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ABSTRACT

Responding to accelerating climate change impacts requires broad and effective engagement with stakeholders, at multiple geographic and governance levels. Stakeholder participation has been hailed as a facilitated approach in climate change adaptation that supports social learning, depolarization of perceptions, and fosters collective action. But stakeholder participation remains loosely interpreted and evaluating measures are limited. This study employs social network analysis (SNA) to investigate how social relations among stakeholders, which emerge as a result of participation, are associated with stakeholder learning, as changes in perceptions of climate change. We hypothesized that reciprocal ties of understanding, respect, and influence can predict changes in perceptions of climate change. This approach was applied to a case study in Deal Island Peninsula, Maryland (USA) where local residents, scientists, and government officials met from 2016 – 2018 to collaboratively manage the impacts of sea-level rise in their communities. We found that social relations based on mutual *understanding, respect and influence* are positively associated with perceptions of climate change. We provide a detailed conceptualization and implementation of a network-based approach that may serve as a potential quantitative performance measure of stakeholder participation processes in climate change adaptation. Overall, this study provides empirical evidence of the role that emerging social relations have on enhancing or constraining social learning among stakeholders in the Deal Island Peninsula project.

1. INTRODUCTION

Climate change is increasingly portrayed as a complex, 'wicked' environmental problem (Balint et al., 2011; Markowska et al., 2020). Developing local responses to climate change requires flexible, adaptive strategies based on a holistic understanding of climate change, its drivers and impacts, and the governance structures at varying geographic scales (Pasquier et al., 2020; Teodoro and Nairn, 2020). Stakeholder participation is increasingly seen as a key factor in acquiring a more holistic understanding of complex environmental problems (Baird et al., 2016; Calliari et al., 2019; Pasquier et al., 2020; van Aalst et al., 2008) and developing well-informed local governance responses to climate change impacts (Calliari et al., 2019; Shackleton et al., 2019). Stakeholder participation facilitates knowledge innovations (Cvitanovic et al., 2019; Rathwell et al., 2015), is fundamental for social learning processes (Cundill and Rodela, 2012; Lankester, 2013), and builds social ties among diverse stakeholders (Cockburn et al., 2016; Macgillivray, 2018). Yet evaluating stakeholder participation efforts can be difficult as evaluation frameworks vary across different case studies and research contexts (see Hassenforder et al., 2016). As such, understanding the link between stakeholder participation and its targeted outcomes could be strengthened by frameworks and evaluations that cut across a wide range of cases.

In this paper, we employ exploratory research to evaluate how stakeholder participation facilitates social learning in climate change adaptation. In constructing our evaluation framework, we draw upon the environmental management (EM) literature pertaining to processes of participation, social networks, and social learning. We apply this framework to a 2.5-year collaborative research project (2016 – 2018) taking place in Chesapeake Bay, USA. Here, researchers from multiple disciplines actively engaged, via a range of workshops and meetings, with community residents and government employees to collaboratively construct a vulnerability-resiliency assessment of the area (Paolisso et al., 2019). Evaluation of the effects this project had on stakeholders' learning and social networks occurred through an online survey, which was administered at the beginning, middle, and end of the project. This survey measured stakeholders' climate change perceptions, as well as a range of social ties to one another. Data gathered from this survey was then compiled and submitted to a network panel linear modeling framework, to assess the extent to which individual stakeholders' perceptions corresponded to the perceptions of others with whom they had social ties. In what follows, we first summarize the literature informing our evaluation framework, and then proceed with a description of our research site, measures, analyses, and results. We conclude with a reflection on how our results link to the larger body of literature on stakeholder participation and social learning, calling attention to the important role played by social networks.

2. CONCEPTUAL FRAMEWORK

Our basic premise is that stakeholder participation leads to social interaction and the formation of social ties, and in turn, these interactions and ties lead to social learning on the individual level. By *stakeholder participation*, we mean the process in which all relevant actors engage to discuss a management objective and is guided by a philosophy of empowerment, equity, trust, and learning (Anggraeni et al., 2019; Reed, 2008). This participatory process aims to systematize knowledge in a way that is useful to practitioners and scientists (Schwilch et al., 2012). *Social ties* refer to the relations linking individuals together and can range from those based on social interaction to relations based on respect and understanding. Finally, *social learning* refers to an individual's change in perceptions or beliefs as a result of being exposed to the perceptions or beliefs of others within a participatory group (van der Wal et al., 2014). In what follows, we summarize the literature linking these processes together.

2.1 Participation and social networks

Environmental management studies indicate that engaging stakeholders in participatory processes provide unique opportunities for stakeholders to interact face-to-face and share their views (Daniels and Walker, 2001; Lumosi et al., 2019; Paolisso et al., 2019). Such interactions form channels through which information can flow (Ernoul and Wardell-Johnson, 2013), and mutual understanding to occur (Rist et al., 2006). In addition, these interactions can lead to the formation of collaboration ties (Anggraeni et al., 2019; Baird et al., 2018; Bodin and Crona, 2009; Kochskämper et al., 2016; Masuda, 2007), and ties based on trust and/or respect (Cundill and Rodela, 2012; García-Nieto et al., 2019). The field of social network analysis (SNA) has increasingly been adopted within the EM field as a means for capturing such relations (Bodin, 2017; Bodin and Prell, 2011). The application of network analysis has tested the extent to which participation leads to tie formation among stakeholders (Baird et al., 2016; Plummer et al., 2017a), as well as a means for identifying diverse stakeholders in participatory processes (Prell et al., 2011).

In this study, stakeholder participation is practically seen as the number of times stakeholders attend project workshops and meetings in which they engage in collaborative decision-making processes. A substantive amount of work has been done in the methods for identifying heterogenous stakeholders who represent different aspects of the social-ecological system in focus, with keen attention to the inclusion of minorities and/or marginalized groups (Colvin et al., 2016; Hauck et al., 2016; Prell et al., 2008). Once stakeholders are identified and participate (i.e,. attend meetings), it is expected that social ties will be formed and strengthened across stakeholder groups. The dynamics of connectivity are capture and studied through the use of SNA.

2.2 Participation and learning

EM research adopting an SNA approach also indicates that social networks act as moderating mechanisms that lead to stakeholder learning (Cundill and Rodela, 2012; Lankester, 2013; Schwilch et al., 2012). Here, social ties are seen as conduits for explicit and implicit information flows regarding environmental problems and management issues (Sandström et al., 2014), which exposes stakeholders to the perceptions and beliefs of others and may lead them to modify their views and/or behaviors regarding an environmental issue (Crona et al., 2011; Muter et al., 2013). Such a process of linking, sharing information, and modifying one's views and/or behavior is referred to as social contagion (Burt, 1987). Leenders (2002) operationalized social contagion as a result of an individual's embeddedness in a social network, where *embeddedness* refers to the degree to which an individual is linked to others within a bounded set network of actors (e.g., participatory workshops). As the level of embeddedness increases for an individual, so is the likelihood of that person changing his/her views based on the views of networked partners, thus enabling the process of social contagion to occur (Burt, 1987; Doreian et al., 1989; Leenders, 2002).

Studies across a range of empirical contexts have given support for social contagion (e.g., Christakis and Fowler, 2013; Friedkin, 2001; Marsden and Friedkin, 1993). In the context of EM, Muter et al. (2013) found evidence for contagion happening between experts and laypeople regarding their perceptions of wildlife conservation. In particular, they found that having more and stronger communication ties between experts and laypeople made them more likely to share similar perceptions about wildlife management. Prell et al. (2010) and de Nooy (2013) found similar results when evaluating how stakeholders share similar knowledge, values, and perceptions with communication partners. However, not all types of knowledge, values, and perceptions have the same degree of contagion, as individuals may seek only certain types of information from their networked partners but not others (de Nooy, 2013). Similarly, Matous and Todo (2015) found that information-exchange ties among farmers led to the diffusion of composting practices in Ethiopia. As such, social networks can lead to more than the contagion of knowledge and perceptions, it may lead to behavioral changes in environmental management (Matous and Todo, 2015).

Social contagion can occur via *different* types of social networks, but not necessarily in *all* kinds of networks. For example, Muter et al. (2013) showed that some perceptions were not associated with communication ties but did not discard the possibility that actors may have been influenced by other, unobserved, networks. Other studies indicate that relations containing a more social dimension (e.g. friendship or social rapport) tend to lead to contagion processes more readily than relations based solely on instrumental pursuit (Prell and Lo, 2016; Uzzi and Lancaster, 2003). As such, studies that only consider one social network, such as communication (de Nooy, 2013; Prell et al., 2010), collaboration ties (Bodin, 2017; de Klepper et al., 2010), or advice (Freitag et al., 2018; Gibbons, 2004; Matous and Todo, 2015), may only provide partial views of social contagion within the scope of a single network. Gathering data on multiple networks may enable a study to better capture the variety of social processes linking stakeholders together (Hauck et al., 2016; Therrien et al., 2018). Thus, providing a deeper, more nuanced understanding of the dimensionality of the social processes influencing perceptions and behavior.

In this study, we present a quantitative SNA approach that captures specific relational networks among stakeholders arising out of a participatory process. These ties are based on understanding, respect, and influence. Ties based on understanding are those in which actors believe other actors in the network understand their views, beliefs, and/or values. Such ties are expected to increase among stakeholders as a result of participatory practices (Lumosi et al., 2019; Mostert et al., 2007; Reed et al., 2010; Rist et al., 2006; Schwilch et al., 2012). Similarly, ties based on respect are those in which stakeholders feel that other participants respect their views, beliefs, and values, and again, the participation literature notes the importance of maintaining and strengthening respect among stakeholders via the participatory process (Kocho-Schellenberg and Berkes, 2015; Rathwell et al., 2015; Rist et al., 2006). Finally, ties based on influence are those in which stakeholders feel that other participants have influenced their views, beliefs, and values. The literature refers to influence in participation as the relative power some individuals have to influence others (Ceddia et al., 2017; Hauck et al., 2016, 2015; Schiffer and Hauck, 2010). Collectively, this range of networks aims to capture the multidimensionality of cognitive relationships that arise among stakeholders via participation, and then tests the extent to which these relations (individually or collectively) lead to contagion. Yet in addition, we also capture the varying strength of ties for each relation. Tie strength refers to the degree of emotional intensity, intimacy, and reciprocity of a social tie between two actors (Krackhardt et al., 2003), and may be captured through a Likert scale item. In the literature, stronger ties are often linked to stakeholder influence and mutual learning (Prell et al., 2009), while weaker ties are linked to access to new information (Granovetter, 1983). For contagion processes, stronger ties between two actors in a network increase the likelihood of both adopting similar views and behaviors (Muter et al., 2013).

An additional network of interactions between stakeholders outside of the participatory process was gathered to control for potential contagion from outside project sources. The distinction between interaction-based and cognitive networks is not fully understood in the literature. As such, this study may also contribute in filling this gap in the literature.

Taken together, the evaluative approach presented here advances the work linking social networks to EM outcomes in a number of key respects. First, we capture greater complexity by measuring a range of networks, over time, among the same set of actors. These networks, moreover, also capture the varying strength of ties linking actors together. As such, by quantitatively measuring network multiplexity and varying tie strength, over time, we bring a level of precision to EM studies that aim to capture complex social processes and their outcomes. Second, we measure the impact that stakeholder networks, formed through participatory processes, have on individual learning by linking these two via a contagion approach that directly accounts for stakeholders' ties and the perceptions of networked partners. In this way, our approach advances the measurement of learning from perception-based measures to one that accounts for the role of social relations. Finally, this approach is embedded within a transdisciplinary research project, where scientists engaged directly as part of the research project, in this way, this knowledge can be facilitated to practitioners and other stakeholders that may employ a similar approach in different regions.

3. MATERIALS AND METHODS

3.1 Study Area

To address the aim of this study, we selected a case study with the participatory conditions needed to test our methodology. The Deal Island peninsula is located on the Eastern Shore of Maryland, USA, along the Chesapeake Bay. The peninsula covers an area of approximately 18 square miles, inhabited by about 1000 people. Given the ideal location at the shore, the main source of income is from harvesting seafood, mainly crabs (*Calliencecus sapidus*) and oysters (*Crassostrea virginica*), and many of the inhabitants' families have lived similar lifestyles on this island for many generations over the last 300 years. The island is experiencing an increase in flooding and coastal erosion related to a changing climate (Paolisso et al., 2019). Projections of future climate change in the Chesapeake Bay show, among others, an increase in sea-level rise, storm frequency and severity, flooding, and erosion (Teodoro and Nairn, 2020). In light of these impacts, community members have sought out for support from county and state government (Paolisso et al., 2019). As a result, a network of stakeholders including scientists, local and state government representatives, and residents have established the Deal Island Peninsula Partnership (DIPP), which aims to reduce the vulnerabilities of the Deal Island Peninsula area to the climate impacts by creating partnerships between communities and relevant stakeholders through a collaborative science and learning approach (Miller Hesed et al., 2020). We chose this area because of DIPP's focus on climate adaptation and its goal to facilitate learning across a diverse set of stakeholders.

DIPP stakeholders were invited to participate in the Integrated Coastal Resilience Assessment (ICRA) project, which aimed to bring stakeholders together, via a number of collaborative activities, to identify geographic areas of concern on the Deal Island peninsula, document the vulnerabilities and resilience within these areas, and identify a list of adaptation strategies. Initial participants were invited from previous DIPP engagements and notices were placed in community centers, newspapers, and mail to invite all interested persons to the project events.

3.2 Data collection and data characteristics

Online surveys were distributed to active ICRA participants, which collected data three times between 2016 –2018. The survey was divided into two main components: a part of the perceptions of climate change and another part of the social ties between stakeholders. The questions on perceptions included seven 4-point Likert statements on climate change (Table 1). Participants were asked to rate the statements depending on how much they agreed or disagreed with each statement. Individual statements were intended to gauge the perceptions of the respondent on climate change awareness, risks, and actions. The responses had high internal reliability (Cronbach $\alpha = 0.96$) and were combined into a single averaged score. This score can be interpreted as a person's overall level of awareness of the causes and impacts of climate change in their community.

1. The climate is changing in different ways from before due to the impacts of human activities.
2. Climate change is affecting the communities of the Deal Island Peninsula already.
3. Climate change is affecting the environment of the Deal Island Peninsula already.
4. The Deal Island Peninsula area will experience more storms and floods in the future due to climate change.
5. The resilience of Deal Island Peninsula communities will be reduced in the future due to climate change.
6. Climate change is a significant threat to the social and ecological system of the Deal Island Peninsula.
7. Building relationships with people and organizations that have an interest in the Deal Island Peninsula and can help communities cope with climate change.

Table 1. Questions for measuring perceptions of climate change in the survey

On the social networks section of the survey, participants were asked to provide information about four types of social relations they held with other participants in the DIPP (Table 2). A roster was provided to each respondent with the names of all other DIPP members, and respondents were asked three Likert scaled network questions (where 1 = 'a little', 2 = 'somewhat', 3 = 'a lot', 0 = non-existent) pertaining to perceived feelings of understanding, respect, and influence (see Table 2). These three network measures were included to gauge how feelings of respect, understanding, and influence changed over time as a result of DIPP participation. However, as some participants had more face-to-face interaction outside of DIPP meetings than others (e.g. they were neighbors or worked at the same organization), we also included this interaction network as a control measure to take into account the extent to which stakeholders interacted with others outside of the DIPP (see question 4, Table 2).

Type of network	Network question in the survey
1. Understanding	This person understands my views regarding the DIPP area.
2. Respect	I feel this person respects my views/ beliefs regarding the community and environmental problems facing Deal Island.
3. Influence	This person has influenced my understanding of the community and environmental problems affecting the DIPP area.
4. Interaction	Do you interact with this person outside the project?

Table 2. Social relations data and corresponding survey questions

Additional control data collected via the survey included age, gender, income level, and stakeholder category (i.e., whether a person was a local, a government official, or a scientist; see Table 3). By including the stakeholder category as a dummy variable, we were able to isolate the network effects within stakeholder categories.

	T = 1 (N = 53)	T = 2 (N = 52)	T = 3 (N = 42)
Stakeholder Type			
Local	19	19	19
Scientists	13	12	8
Government	21	20	14
Age			
Mean	42.21	52.77	52.83
Min	29	29	29
Max	79	79	75
Gender			
Male	31	28	22
Female	22	24	20
Income (1 – 9)			
Mean	4.51	5.81	5.80

Table 3. Longitudinal qualities of collected data.

3.3 Operationalizing social contagion

Social ties are commonly represented in SNA as a square matrix (W), where all stakeholders sending ties are represented in rows (W_i) and stakeholders receiving ties are represented in columns (W_j). The tie value between any pair of stakeholders is represented in matrix W as nonzero W_{ij} values.

Although most network studies focus on binary networks, modeling empirical networks in which the strength or intensity of tie varies could provide greater insights into the social system under question, and a richer understanding of the social relationships overall (Barrat et al., 2004). In our dataset, although we captured ties ranging from weak, i.e. where respondents gave their relationship with another participant a ranking of 1 ('little'), to moderate, i.e. with a ranking of 2 ('sometimes'), and strong, i.e. where respondents ranked the strength of a tie as 3 ('a lot'), for modeling purposes, we discarded all weak ties from the dataset, and only included those ties with a rank of moderate ('sometimes') or strong ('a lot'). This decision to discard weak ties was based on the fact that (i) past SNA research has shown, across an array of empirical contexts, that stronger ties are good in the implementation of conservation and adaptation actions (Barnes et al., 2017; Bodin et al., 2019; Weenig and Midden, 1991), and (ii) stronger ties are better predictors of changes in views among stakeholders because a person is more likely to adopt the views of someone they trust and share a degree of intimacy (Prell et al., 2010). The strength of a tie may affect the perceptions of actors in different ways depending on the number of ties a given actor holds with others and the perceptions of those others (Figure 1).

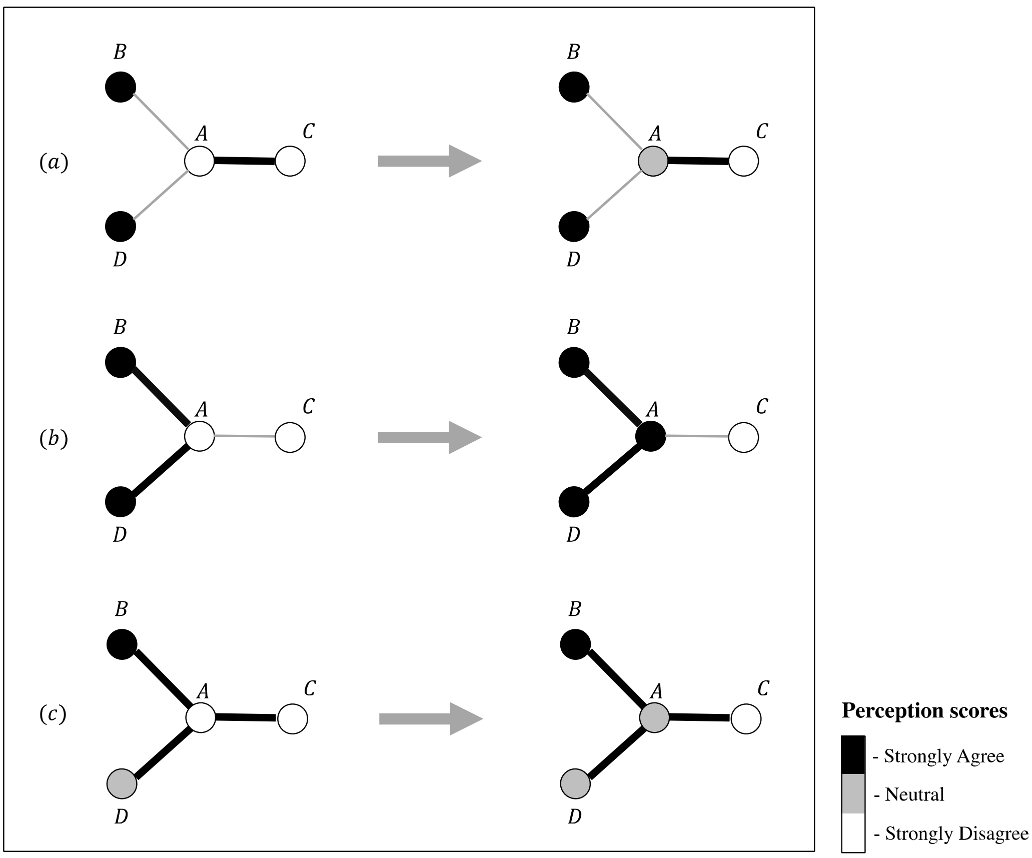

Figure 1. Different settings where strong ties may impact perceptions over time: (a) a strong tie may counteract influence from others, (b) strong ties with actors with drastically different views may accelerate a rapid change in perceptions, (c) strong ties with actors with varying degrees of perceptions may lead to a moderate change in perceptions.

In addition to discarding weak ties from our dataset, we also discarded non-reciprocated links, following Krackhardt et al. (2003). The decision for focusing on reciprocal ties was founded, firstly, on the emphasis placed in participatory literature, and on the importance of *mutual* learning in participation (Bhattachan et al., 2018). This means that the exchange of knowledge among stakeholders is expected to be a two-way exchange based on understanding, respect, and/or influence (Bhattachan et al., 2018; Rathwell et al., 2015; Rist et al., 2006).

Our resulting matrix thus consisted of valued, reciprocal ties among stakeholders, where a 1 = moderate, and 2 = strong ties. Additionally, following suggestions of Leenders (2002), we normalized W by row, which transforms the network ties into weights distributed to all of the ego's outgoing ties and whose sum equals 1 for all stakeholders. The row-normalization is applicable when the goal is to limit the incoming influence for all stakeholders. However, by doing this we do not consider the influence people exert on others. This approach was used because of our focus on individual learning. Using this transformed W matrix, we can then operationalize influence using the following formula:

(1) $$A_{rt} = W_{rt} \;\; {}_{t}$$

Where A_{rt} contain the variables of influence for each social relation (*r*) in period *t*, W_{rt} are distinct network weighted matrices (four in our case) in period *t*, and   is the vector of climate change perception scores for all stakeholders in period *t*. This multiplication generated a vector of weighted sums of perceptions to which each stakeholder was exposed. After computing the influence variables (A_{rt}) we introduced it to a network panel linear model (formula 2) to evaluate the effect each network (*r*) has on climate change perception scores:[1]

(2) $${}_{it} = \;\; A_{rt} + \;\; {}_{2}x_{it} + a_i + \varepsilon_{it}$$

where *i* = 1, ..., n is the individual stakeholder index, *t* = 1, …, *T* is the time index, a_i is the individual unobserved effect, and ε_{it} a random disturbance term of mean 0. We assume that the unobserved effect a_i is uncorrelated with the explanatory variables (independent of all explanatory variables in all periods) and we consider the network as non-random and exogenous, following Jochmans and Wiedner (2019). The analysis was done using the *plm* routine in R package *plm* (Croissant and Millo, 2008). This modeling approach was adequate

[1] This model is akin to network autocorrelation models (Doreian, 1989; Leenders, 2002) for longitudinal data.

to deal with changes in the network size at every data collection period, addressing an important challenge in the study of stakeholder participation processes over time.

4. RESULTS

In this section, we first present the descriptive results for each social network and the corresponding variable of influence. Then, we present the modeling results for each social network as well as the results of a combined model.

4.1 Descriptive network-level data

Descriptive measures were computed to characterize the structure of our social relationships (Table 4). Summary statistics of each network include (1) the density, which refers to the size and level of connectivity in a network (i.e., the ratio of existing ties and the number of all possible ties); (2) the average degree centrality, which is the average number of reciprocal ties for all stakeholders at any given time; (3) its centralization, which indicates the level of hierarchy present in the network; and (4) the number of total ties in each network. These measures are descriptive indicators of social connectivity and provide information on the network dataset used in this analysis.

Networks	Waves	Ave. Centrality (SD)	Centralization	Density	Total ties
Understand					
	Wave 1:	2.98 (3.35)	0.367	0.057	158
	Wave 2:	3.85 (4.02)	0.370	0.075	200
	Wave 3:	6.00 (5.72)	0.613	0.146	252
Respect					
	Wave 1:	3.17 (3.70)	0.529	0.061	168
	Wave 2:	4.31 (4.32)	0.406	0.084	224
	Wave 3:	6.09 (5.74)	0.743	0.148	256
Influence					
	Wave 1:	2.19 (2.99)	0.409	0.042	116
	Wave 2:	2.19 (3.21)	0.292	0.043	114
	Wave 3:	3.62 (4.32)	0.487	0.088	152
Interaction					
	Wave 1:	2.38 (2.33)	0.138	0.048	126
	Wave 2:	3.08 (2.71)	0.241	0.060	160
	Wave 3:	2.95 (2.65)	0.254	0.072	124

Table 4. Summary of reciprocal network-level descriptive statistics

Looking at the structural characteristics of the social network (Table 4), we observed the following: both the *Understanding* and *Respect* networks follow similar trends over time. Their sizes grew in similar proportions as shown by their densities and number of ties. Their average degree jumps to 6.00 and 6.09 at period 3 for *Understanding* and *Respect* networks, respectively; making these networks the ones with the most connectivity increase in our data. The centralization scores of *Understanding* and *Respect* networks differ in that *Respect* drops to 0.406 in wave 2, compared to a 0.529 in wave 1. Similarly, the centralization score of the *Influence* network drops to 0.292 in wave 2, compared to 0.409 in wave 1. This drop in centralization scores in wave 2 indicates that the distribution of ties, for both social relations, became more even and less centered around a few, dominant stakeholders. Other measures of the *Influence* network show a similar size and centrality for wave 1 and 2, and an increase on all measures in wave 3. The *Interaction* network shows a steady composition throughout the three periods. Its size, centrality, and centralization remain roughly consistent, and one might interpret this as an indication that ICRA activities did not lead to greater interactions outside project meetings, but rather, such outside interactions were separate from ICRA related events. Its lower centralization score compared to other networks suggests informal interaction ties are spread out among stakeholders and that there is no central group of actors that everybody interacts with outside the project.

Perceptions of climate change are mostly within the upper side of the scale—most actors hold climate change perception scores between 3 and 4 (4 = "strongly agree"). The generally high level of climate change perceptions in our dataset was expected, given that most stakeholders in DIPP had been meeting and collaborating for a few years before the ICRA data was collected. A visualization of the level of climate change perceptions to which stakeholders were exposed is shown in Figure 2.

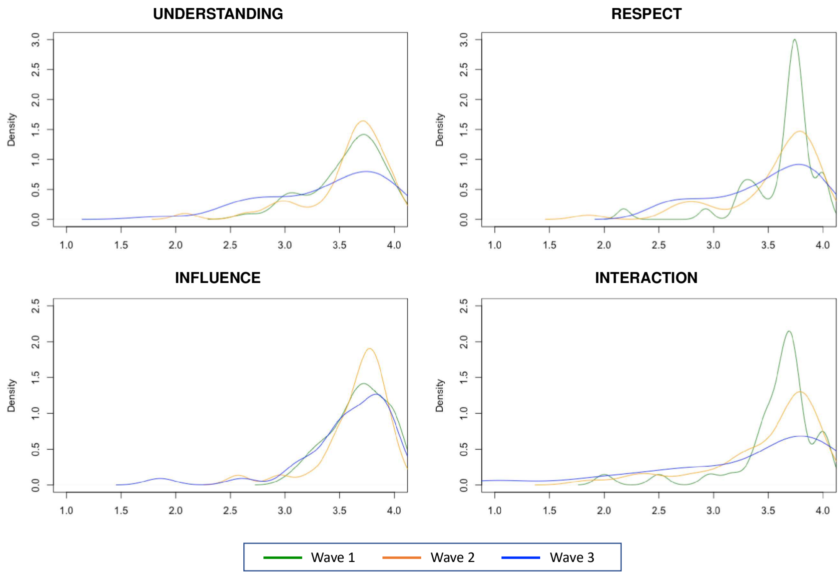

Figure 2. Density plots of overall perceptions of climate awareness to which stakeholders are exposed to divided by data periods.

The majority of respondents (60%) in our sample were exposed to high levels of climate change perceptions. This pattern is true for all networks at all periods, with some important nuances. First, the *Understanding* network shows a decreasing trend in the proportion of people exposed to high levels of climate change perceptions, from 67.8% in period 1 to 61.9% in period 3. A decreasing value may be seen as a positive outcome, given that more *Understanding* ties may have been formed between stakeholders with initially different views on climate change (e.g., scientists reporting they felt understood by locals). On the other hand, the *Respect* and *Influence* networks show an increase in the proportion of people exposed to high levels of climate change perceptions from period 1 (66% and 60%) to period 3 (69% and 70%), respectively. An interpretation of this may be that more people reported being respected and influenced by individuals who reported high scores of climate change perceptions (e.g., locals increasingly reporting they felt respected and influenced by scientists). The network of outside-project interaction shows some variability in the proportion of stakeholders influenced by high levels of climate change perceptions, but with no recognizable trend.

4.2 Panel model results

The results of models (1) – (10) in Table 5 show that the individual social networks based on reciprocal understanding, respect, influence, and interaction outside of the project, predict a statistically significant and positive relationship with the levels of climate change perceptions among stakeholders. When looking at the effects of control variables (age, gender, income), we see that age is consistently significant in the full model of all networks. Age's negative coefficient suggests that older respondents are more likely to have lower climate change perception scores when controlling for all other effects and social networks. In the literature, the relationship between age and perceptions of climate change is inconclusive, with some finding a positive relationship (Apata et al., 2009) and others a negative (Aphunu and Nwabeze, 2013). Here, we show that age is indeed a significant predictor of climate change perceptions, with a negative relationship. Income is significant in the *Influence* network, suggesting that individuals with high income are more likely to have higher levels of climate change perceptions.

When looking at stakeholder characteristics (i.e., stakeholder type), belonging to a local resident category was only significant in the base models but became insignificant in the full models for all networks. The dummy variable for data period 3 (*t3*) was significant in the *Understanding* and *Respect* networks; suggesting that on that period of data collection, a significant number of understanding and respect ties were created that facilitated the influence of perceptions of climate change.

	Predicting: Perceptions of Climate Change										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Social networks effects:											
Understanding	0.484***	0.448***	0.491***								0.297
	(0.105)	(0.102)	(0.104)								(0.242)
Respect				0.514***	0.493***	0.540***					0.036
				(0.125)	(0.121)	(0.123)					(0.276)
Influence							0.358***	0.415***	0.424***		0.228*
							(0.133)	(0.129)	(0.128)		(0.135)
Interaction										0.436***	0.337**
										(0.090)	(0.170)
Control variables:											
Research	0.029	0.190	0.179	0.047	0.191	0.187	0.099	0.280	0.273	0.251	
	(0.171)	(0.172)	(0.173)	(0.170)	(0.167)	(0.168)	(0.219)	(0.205)	(0.208)	(0.169)	
Local	-0.616***	-0.289	-0.305	-0.569***	-0.259	-0.255	-0.792***	-0.356	-0.366	-0.125	
	(0.194)	(0.209)	(0.209)	(0.192)	(0.205)	(0.205)	(0.239)	(0.241)	(0.244)	(0.209)	
Age		-0.011**	-0.011**		-0.010**	-0.011**		-0.013***	-0.014***	-0.014***	
		(0.004)	(0.005)		(0.004)	(0.004)		(0.005)	(0.005)	(0.005)	
Gender		-0.165	-0.141		-0.212	-0.188		-0.209	-0.198	-0.122	
		(0.155)	(0.156)		(0.146)	(0.147)		(0.183)	(0.185)	(0.148)	
Income		0.040	0.034		0.032	0.028		0.066**	0.063*	0.011	
		(0.029)	(0.029)		(0.028)	(0.029)		(0.033)	(0.033)	(0.029)	
t2			0.068			0.087			0.104	0.062	
			(0.067)			(0.069)			(0.077)	(0.059)	
t3			0.151**			0.137*			0.101	0.091	
			(0.074)			(0.074)			(0.081)	(0.067)	
Constant	1.849***	2.271***	2.094***	1.737***	2.150***	1.958***	2.195***	2.291***	2.245***	2.598***	0.252
	(0.402)	(0.445)	(0.452)	(0.473)	(0.497)	(0.508)	(0.516)	(0.575)	(0.575)	(0.405)	(0.659)
Observations	112	111	111	115	114	114	92	91	91	110	84
R^2	0.391	0.447	0.466	0.382	0.447	0.463	0.314	0.416	0.427	0.494	0.399
Adjusted R^2	0.374	0.415	0.425	0.366	0.416	0.422	0.291	0.375	0.371	0.454	0.369
AIC	31.85	27.54	24.37	34.39	32.82	31.07	23.99	23.12	21.59	-4.14	15.452
F Statistic	64.192***	80.145***	85.077***	65.764***	84.017***	87.887***	33.868***	54.740***	56.266***	97.937***	48.877***

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

***Table 5**. Social network effects show a significant relationship with climate change perceptions in network panel modeling frameworks with prominent control variables.*

Model (11) in Table 5 indicates that when modeled jointly, although all social network effects are positive, only the reciprocal networks of *Influence* and *Interaction* have a significant association with climate change perceptions. This may be because stakeholders can aptly identify those others that have influenced them the most, and thus the relation between influence ties and actual influence in perceptions are stronger than those of understanding and respect. In model (11), no other covariates were included to increase the degrees of freedom given the smaller number of observations. The number of observations decreases in Model (11) because it includes only the observations that have responses in all four networks.

5. DISCUSSION

The goal of this study was to investigate the effect that social networks have on social learning, which we defined as a change in perceptions in stakeholder participation. Specifically, we constructed variables to capture the social contagion process from different social networks that emerged during a stakeholder participatory process. This paper focused on multiple, valued social networks that are believed to be important aspects of stakeholder participation. Results show that reciprocal networks of *Understanding*, *Respect*, *Influence*, and *Interaction* have a statistically significant and positive relationship with perceptions of climate change among ICRA stakeholder participants. Thus, stakeholders in our study aligned their climate change views with those of their networked partners, across a range of social relations. These results provide implications for researchers and practitioners in climate change adaptation: namely in the management of stakeholder engagement processes. The methodological approach presented in this study may be replicated elsewhere to expand our findings and as an evaluation tool. Stakeholder participation is costly and time-consuming, and achieving its desired outcomes requires long-term commitments from all parties involved. However, our study shows that networks can capture social dynamics associated with learning even in 2.5 years.

The understanding network seems to be a reliable predictor of climate change perceptions among DIPP stakeholders. Asking individuals if they felt understood by other participants involves asking them about their experience within the participatory process, which goes beyond a simple connection. Indeed, feeling understood is a sign that, regardless of stakeholder type, individuals care about being able to express themselves and feeling like others acknowledge their views and understand them (Lauer et al., 2017). Reciprocal ties of understanding translate to mutual-understanding, which has shown to be a viable social dynamic that facilitates learning (Lumosi et al., 2019). Similarly, our results show that feeling respected by and respecting other individuals are also social processes that support learning in stakeholder participation. In the case of the ICRA participants, feeling understood and respected showed similar results. Certainly, one could argue that both mutual understanding and mutual respect contribute to an inclusive atmosphere in heterogeneous participatory projects (de Vente et al., 2016). Moreover, mutual influence in the joint model (11) showed a statistically significant and stronger effect than that of understanding and respect ties, which suggests that asking stakeholders to identify those who had influenced their understanding of the community and environmental problems in the DIP area is a direct and meaningful approach to map how the contagion of perceptions spreads through a network. Mutual-influence ties between individuals who have different, often opposing, views suggest that participatory projects like the ICRA can facilitate the formation of cognitive ties based on understanding and respect that support learning among a set of heterogeneous individuals. For example, scientists may learn about the local priorities and challenges directly from local residents who, in turn, may become more open to scientific information if they feel respected and understood by scientists. As a result, both may be open to learning from each other.

In our study, we used an *Interaction* network as a control to capture those social processes, outside the ICRA project, that may impact perception changes among stakeholders. The fact that the *Interaction* network was significant echoes previous studies that had considered the role of communication and interaction ties on actors' environmental perceptions (Gore et al., 2009; Jasny et al., 2015; Prell et al., 2010; Scherer and Cho, 2003). In addition, controlling for these outside-ICRA interactions was important, as it helped tease apart the impact of *outside*-ICRA project interactions from cognitive processes taking place *within* the ICRA project. By finding support for both *within*- and *outside*-project relations, our study demonstrates that outside interactions *may* contribute to contagion processes, yet they certainly do not replace the influence that cognitive relations (i.e. mutual understanding, respect, and influence), engendered via stakeholder participation, have on participants learning from one another and becoming more similar in their perceptions overtime. As such, our results advance the literature on participation and learning by offering greater precision on the comparative role of within-project relations alongside outside-project interactions. As of this writing, we are unaware of any study in the participatory literature that accounts for such an array of competing tendencies as those we tested here.

This study's findings suggest that a participatory process that nurtures an atmosphere where stakeholders increasingly feel understood, respected, and open to the influence of others is conducive for learning. The fact that all networks show significance in predicting perceptions of climate change show that the multidimensional nature of social relations can, and should, have an impact on contagion processes (Prell and Lo, 2016; Uzzi and Lancaster, 2003), and hence, be measured in stakeholder participation. Several scholars have argued that the quality of outcomes depends greatly on the quality of the participatory process (de Vente et al., 2016; Plummer et al., 2017b), and our findings supplement this, by showing which kinds of social relational processes matter. Networks of understanding, respect, and influence, enabled by participatory processes, highlights the positive impact that stakeholder engagement can have in developing larger, stronger, and diverse networks that may increase the adaptive capacity of a community to climate changes (Anggraeni et al., 2019; Cundill and Rodela, 2012).

Our results show that the level of climate change perceptions is the highest in the scientist group, moderately lower in the government official group, and the lowest in the local resident group, although the difference is not significant among the first two groups and is not statistically robust among the first and third group. This may be attributed to the limited number of categories stakeholders could belong to. If a greater distinction would have been made between different levels of government, for example, or the inclusion of additional stakeholder sub-groups (e.g., local residents and seasonal residents, or municipal government and state government), it is possible that inter-group differences may become more visible. However, previous research has shown that perceptions of environmental issues are not necessarily correlated to the type of stakeholder or their institutional affiliation (Prell et al., 2010).

We have presented a model-driven approach as a viable means of capturing social learning within stakeholder participation. This approach draws from a long tradition of network autocorrelation models that used valued network data and assigns weights to the ties each stakeholder hold (e.g., Dekker et al., 2007). The approach presented here can be applied in different cases and contexts where learning is the desired outcome in participatory processes. We suggest that this framework is more appropriate in stakeholder participation projects where network data collection is accessible. Our measure of social contagion directly links learning to social ties that are established or strengthened during participation. In this way, we separate ourselves from common measures, such as Plummer et al. (2017a), which only include self-reported learning and participatory process variables. Our approach instead is aimed at capturing greater precision in the various social relational processes that may be at work in social learning environments.

This study has important implications for policy-making and management of climate change adaptation. Stakeholder participation is becoming commonplace in climate change adaptation and environmental governance (García-Nieto et al., 2019; Reed, 2008). However, the implementation of these processes is dependent on financial and human resources from funding agencies. In the case of the ICRA project, funding came from the Maryland Sea Grant (MDSG), a state-level research institution that supports participatory science and science-based policy-making. Funding institutions need to justify their investment and provide supporting evidence of the outcomes of participatory projects. We believe that this study enables both researchers and practitioners to think of new ways of measuring social outcomes of participation, like learning. Participatory processes, in effect, are akin to group decision making processes that lead to outcomes. If so, then providing a measure of understanding and respect in relation to social learning within stakeholder deliberations may provide valuable insight into the decision-making process.

This study is not without its limitations and an important one to mention is that we did not evaluate whether participation leads to tie formation. Active participation can be measured by considering the instances where stakeholders were present in participatory events, i.e., the number of times they met throughout the course of the study. Our study did not consider how co-attendance by two stakeholders would lead to tie formation between them, and this is something future research may consider. This framework uses tie strength data as weights in the network analysis (Figure 1). However, our analysis may not have captured a wide enough range of tie strengths, as we only considered two degrees of tie strength (i.e., moderate and strong). The limited range of strength values may have resulted in a marginal difference in the estimation of the contagion process. As such, future work can extend the range of tie strength to more detailed levels and test the specific configurations presented in Figure 1 and the extent to which the tie strength matters when testing for social contagion of perceptions. Moreover, the process and the results of this study do not point concretely on the dynamic interaction between the ties and the perception change. In other words, we cannot assert whether (i) establishing more mutual-understanding ties raises climate change perception scores, or if (ii) individuals with high climate change perception scores establish ties with others that share similar perceptions. To answer these questions between competing hypotheses of social contagion (Burt, 1987; Leenders, 2002) and social selection (McPherson et al., 2001) requires the use of more complicated statistical analyses that can simultaneously test both hypotheses (Stadtfeld et al., 2018).

In this study, stakeholder participation partly emerged from pre-existing social ties among ICRA participants and was partly driven by individuals' decision to participate after becoming aware of the project's existence. It is therefore important to expand on the possible effects of participation bias in our data. It is possible that participants in the ICRA project were more willing to engage in collaborative and learning experiences than others who chose not to participate or dropped out from the project. One way that a learning bias is controlled for is by including multiple perceptions. Muter et al. (2013) collected a control perception from respondents and showed that even in the same set of participants, influence does not occur for all perceptions. In this study, we only measured climate change perceptions and therefore were not able to include a control perception variable. Our modeling approach is not compromised by this limitation given that (i) our network analysis does not assume independence of observations and we introduce the influence variables (A_{rt}) to capture the inter-dependence of the observed climate change perception scores, and (ii) because previous studies have showed that learning or influence in perceptions cannot be assumed to be biased by participation (Muter et al., 2013).

It would be relevant to employ a study of this sort to a participatory context at an earlier stage of engagement, where stakeholders do not have pre-existing social contact and test the time it takes for social learning to be picked up by an evaluation framework such as ours. Future research can improve the understanding of social contagion through ties of mutual understanding and respect by testing their predictive power on other types of perceptions (e.g., perceptions of resilience, adaptive capacity, or vulnerability). Also, collecting network and perception data for a longer period may provide insights into the strength of this relationship in longer periods. Moreover, this model would benefit from additional covariates, like educational level of stakeholders, to control for other predictors of perceptions.

Overall, we can interpret these results in the following way: stakeholders that share bonds of mutual-understanding, mutual-respect, and mutual-influence with other stakeholders that have a high level of climate change perceptions are more likely to have a high level of climate change perceptions themselves. The degree to which these networks support the transfer of perceptions (i.e., social learning) can be measured, as we have done in this study, by directly linking changes in perceptions to properties of the collaborative process, namely the set of emerging social networks between stakeholders. As a result, we can assume that a participatory process that fosters mutual understanding, respect, and influence among participants, is likely to increase the similarity of climate change perceptions among these participants. We limit our interpretation of the results to the ICRA stakeholder network. The implementation of stakeholder participation mechanisms is to a large extent locally-bound and addresses local problems with the involvement of locally-relevant individuals. As such, we cannot generalize our findings to all processes that bring about shared understanding and social influence, but we can state that our findings support arguments found in the literature linking participation to learning outcomes. Notwithstanding, this study demonstrates a generalizable model-driven approach for quantifying individual learning across multiple stakeholder participation networks and enriches a growing empirical literature of social contagion and social learning, to which our study adds support for processes of social learning in stakeholder participation in the context of climate change adaptation.

6. CONCLUSION

Responding to accelerating climate change impacts requires broad and effective engagement with stakeholders, at multiple geographic and governance levels. In this study, we tested the relationship that exists between social ties among stakeholders in a participatory process and changes of climate change perceptions (i.e., learning). Our findings suggest that social learning can be partially explained by social ties that are established and nurtured within participatory processes. Specifically, reciprocal ties based on understanding, respect, and influence capture important processes and outcomes characteristic of stakeholder participation. These findings showcase the moderating role of social ties on contagion processes of climate change perceptions.

Our findings add to the environmental management literature in three ways: First, we have shown that social ties among stakeholders are complex and multidimensional, and studies that employ SNA frameworks and tools should account for this complexity. We used three social networks that emerged through participation and a control network for outside the project interaction. In this study, all networks had a positive relationship with perceptions of climate change with *Understanding* and *Respect* networks showing the most growth in time and *Influence* showing the most statistically significant association with climate change perceptions. As such, we have shown that perceptions of climate change may not only be influenced via communication ties, but also through relations based on understanding, respect, and influence. Second, our study provides support for stakeholder participation in showing that it leads to network tie formation among participants. In the case of ICRA, descriptive network statistics showed that mutual understanding and respect increased over time. However, future research may further expand on how different aspects of participation (e.g., co-attendance) may lead to tie-formation. As we have shown, understanding, respect, and influence ties can predict learning, and so our study may be seen as providing a positive evaluation of the ICRA process. Third, our study provides a methodology to evaluate social learning in stakeholder participation that directly accounts for the number and strength of social networks; something that is not common in the EM literature that employs SNA.

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Appendix A - Additional statistical models for robustness

Table A1. Single models for each network - (Pooled)

	(Pooled): ***Climate Change Perceptions***			
	(1)	(2)	(3)	(4)
Interaction	0.554***			
	(0.140)			
Understanding		0.642***		
		(0.196)		
Respect			0.619**	
			(0.285)	
Influence				0.446**
				(0.203)
Age	-0.012**	-0.004	-0.005	-0.005
	(0.005)	(0.006)	(0.008)	(0.007)
Gender	-0.041	-0.204	-0.236*	-0.205
	(0.109)	(0.128)	(0.140)	(0.133)
Income	0.019	0.006	0.013	0.007
	(0.024)	(0.024)	(0.027)	(0.025)
Research	0.180**	0.235***	0.267***	0.219***
	(0.078)	(0.089)	(0.098)	(0.083)
Local	0.001	-0.183	-0.112	-0.341
	(0.212)	(0.222)	(0.276)	(0.223)
t2	-0.051	-0.041	-0.036	-0.004
	(0.126)	(0.123)	(0.125)	(0.118)
t3	0.029	0.031	0.003	0.086
	(0.126)	(0.126)	(0.127)	(0.129)
Observations	121	116	116	129
R^2	0.391	0.362	0.351	0.322
Adjusted R^2	0.348	0.314	0.303	0.277
AIC	208.5796	211.3402	213.7128	236.5874

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2. Overview model of climate change perceptions (dependent variable) and all networks (interaction and perceptual networks).

	Predicting Perceptions of Climate Change		
	coefficient test	*panel linear*	
	(1)	(2)	(3)
Understanding	0.259	0.311	0.297
	(0.852)	(0.235)	(0.242)
Respect	1.003	-0.610**	0.036
	(0.997)	(0.275)	(0.276)
Influence	0.236	0.130	0.228*
	(0.278)	(0.130)	(0.135)
Interaction	-0.067	0.443**	0.337**
	(0.184)	(0.187)	(0.170)
Observations	84	84	84
R^2	0.478	0.279	0.399
Adjusted R^2	0.452	-0.869	0.369
F Statistic	18.114*** (df = 4; 79)	3.102** (df = 4; 32)	48.877***

Note: *p<0.1; **p<0.05; ***p<0.01

REFERENCES

Anggraeni, M., Gupta, J., Verrest, J.L.M., 2019. Cost and value of stakeholders participation: A systematic literature review. Environ. Sci. Policy 101, 364–373. https://doi.org/10.1016/j.envsci.2019.07.012

Apata, T.G., Samuel, K.D., Adeola, A.O., 2009. Analysis of Climate Change Perception and Adaptation among Arable Food Crop Farmers in South Western Nigeria. https://doi.org/10.22004/AG.ECON.51365

Aphunu, A., Nwabeze, G., 2013. Fish Farmers' Perception of Climate change impact on fish production in Delta State, Nigeria. J. Agric. Ext. 16. https://doi.org/10.4314/jae.v16i2.1

Baird, J., Plummer, R., Bodin, Ö., 2016. Collaborative governance for climate change adaptation in Canada: experimenting with adaptive co-management. Reg. Environ. Chang. 16, 747–758. https://doi.org/10.1007/s10113-015-0790-5

Baird, J., Plummer, R., Schultz, L., Armitage, D., Bodin, Ö., 2018. How Does Socio-institutional Diversity Affect Collaborative Governance of Social-Ecological Systems in Practice? Environ. Manage. https://doi.org/10.1007/s00267-018-1123-5

Balint, P.J., Stewart, R.E., Desai, A., Walters, L.C., 2011. Wicked environmental problems: managing uncertainty and conflict. Island Press/Center for Resource Economics. https://doi.org/10.5822/978-1-61091-047-7

Barnes, M., Bodin, Ö., Guerrero, A., McAllister, R., Alexander, S., Robins, G., 2017. The social structural foundations of adaptation and transformation in social–ecological systems. Ecol. Soc. 22. https://doi.org/10.5751/ES-09769-220416

Barrat, A., Barthélemy, M., Pastor-Satorras, R., Vespignani, A., 2004. The architecture of complex weighted networks. Proc. Natl. Acad. Sci. U. S. A. 101, 3747–3752. https://doi.org/10.1073/pnas.0400087101

Bhattachan, A., Jurjonas, M.D., Moody, A.C., Morris, P.R., Sanchez, G.M., Smart, L.S., Taillie, P.J., Emanuel, R.E., Seekamp, E.L., 2018. Sea level rise impacts on rural coastal social-ecological systems and the implications for decision making. Environ. Sci. Policy 90, 122–134. https://doi.org/10.1016/j.envsci.2018.10.006

Bodin, Ö., 2017. Collaborative environmental governance: Achieving collective action in social-ecological systems. Science (80-.). 357. https://doi.org/10.1126/science.aan1114

Bodin, Ö., Crona, B.I., 2009. The role of social networks in natural resource governance: What relational patterns make a difference? Glob. Environ. Chang. 19, 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002

Bodin, Ö., Nohrstedt, D., Baird, J., Summers, R., Plummer, R., 2019. Working at the "speed of trust": pre-existing and emerging social ties in wildfire responder networks in Sweden and Canada. Reg. Environ. Chang. 1–12. https://doi.org/10.1007/s10113-019-01546-z

Bodin, Ö., Prell, C., 2011. Social networks and natural resource management: uncovering the social fabric of environmental governance. Cambridge University Press, New York.

Burt, R.S., 1987. Social Contagion and Innovation: Cohesion versus Structural Equivalence. Am. J. Sociol. 92, 1287–1335.

Calliari, E., Michetti, M., Farnia, L., Ramieri, E., Enrico Mattei Thetis SPA, E., 2019. A network approach for moving from planning to implementation in climate change adaptation: Evidence from southern Mexico. Environ. Sci. Policy 93, 146–157. https://doi.org/10.1016/j.envsci.2018.11.025

Ceddia, M.G., Christopoulos, D., Hernandez, Y., Zepharovich, E., 2017. Assessing adaptive capacity through governance networks: The elaboration of the flood risk management plan in Austria. Environ. Sci. Policy. https://doi.org/10.1016/j.envsci.2017.08.014

Christakis, N.A., Fowler, J.H., 2013. Social contagion theory: examining dynamic social networks and human behavior. Stat. Med. 32, 556–577. https://doi.org/10.1002/sim.5408

Cockburn, J., Rouget, M., Slotow, R., Roberts, D., Boon, R., Douwes, E., O???donoghue, S., Downs, C.T., Mukherjee, S., Musakwa, W., Mutanga, O., Mwabvu, T., Odindi, J., Odindo, A., Proche??, ??erban, Ramdhani, S., Ray-Mukherjee, J., Sershen, Schoeman, M.C., Smit, A.J., Wale, E., Willows-Munro, S., 2016. How to build science-action partnerships for local land-use planning and management: Lessons from Durban, South Africa. Ecol. Soc. 21. https://doi.org/10.5751/ES-08109-210128

Colvin, R.M., Witt, G.B., Lacey, J., 2016. Approaches to identifying stakeholders in environmental management: Insights from practitioners to go beyond the 'usual suspects.' Land use policy 52, 266–276. https://doi.org/10.1016/J.LANDUSEPOL.2015.12.032

Croissant, Y., Millo, G., 2008. Panel data econometrics in R: The plm package. J. Stat. Softw. 27, 1–43. https://doi.org/10.18637/jss.v027.i02

Crona, B., Ernstson, H., Prell, C., Reed, M., Hubacek, K., 2011. Combining social network approaches with social theories to improve understanding of natural resource governance, in: Bödin, O., Prell, C. (Eds.), Social Networks and Natural Resource Management: Uncovering the Social Fabric of Environmental Governance. Cambridge University Press, Cambridge, UK, pp. 44–72.

Cundill, G., Rodela, R., 2012. A review of assertions about the processes and outcomes of social learning in natural resource management. J. Environ. Manage. 113, 7–14. https://doi.org/10.1016/j.jenvman.2012.08.021

Cvitanovic, C., Howden, M., Colvin, R.M., Norström, A., Meadow, A.M., Addison, P.F.E., 2019. Maximising the benefits of participatory climate adaptation research by understanding and managing the associated challenges and risks. https://doi.org/10.1016/j.envsci.2018.12.028

Daniels, S., Walker, G., 2001. Working Through Environmental Conflict: The Collaborative Learning Approach. Praeger Publishers, Westport CT.

de Klepper, M., Sleebos, E., van de Bunt, G., Agneessens, F., 2010. Similarity in friendship networks: Selection or influence? The effect of constraining contexts and non-visible individual attributes. Soc. Networks 32, 82–90. https://doi.org/10.1016/j.socnet.2009.06.003

de Nooy, W., 2013. Communication in Natural Resource Management: Agreement between and Disagreement within Stakeholder Groups. Ecol. Soc. 18, art44. https://doi.org/10.5751/ES-05648-180244

de Vente, J., Reed, M.S., Stringer, L.C., Valente, S., Newig, J., 2016. How does the context and design of participatory decision making processes affect their outcomes? Evidence from sustainable land management in global drylands. Ecol. Soc. 21, art24. https://doi.org/10.5751/ES-08053-210224

Dekker, D., Krackhardt, D., Snijders, T.A.B., 2007. Sensitivity of MRQAP Tests to Collinearity and Autocorrelation Conditions. Psychometrika 72, 563–581. https://doi.org/10.1007/s11336-007-9016-1

Doreian, P., 1989. Network autocorrelation models: problems and prospects, in: Griffith, D.A. (Ed.), Spatial Statistics: Past, Present, and Future. Michigan Document Services, Ann Arbor.

Doreian, P., Freeman, L., White, D., Romney, A., 1989. Models of network effects on social actors. Res. methods Soc. Netw. Anal. 295–317.

Ernoul, L., Wardell-Johnson, A., 2013. Governance in integrated coastal zone management: a social networks analysis of cross-scale collaboration. Environ. Conserv. 40, 231–240. https://doi.org/10.1017/S0376892913000106

Freitag, A., Vogt, B., Hartley, T., 2018. Breaking stereotypes through network analysis of the Chesapeake oyster community. Mar. Policy 90, 146–151. https://doi.org/10.1016/J.MARPOL.2017.12.023

Friedkin, N.E., 2001. Norm formation in social influence networks. Soc. Networks 23, 167–189. https://doi.org/10.1016/S0378-8733(01)00036-3

García-Nieto, A.P., Huland, E., Quintas-Soriano, C., Iniesta-Arandia, I., García-Llorente, M., Palomo, I., Martín-López, B., 2019. Evaluating social learning in participatory mapping of ecosystem services. Ecosyst. People 15, 257–268. https://doi.org/10.1080/26395916.2019.1667875

Gibbons, D.E., 2004. Friendship and advice networks in the context of changing professional values. Adm. Sci. Q. 49, 238–262.

Gore, M.L., Wilson, R.S., Siemer, W.F., Wieczorek Hudenko, H., Clarke, C.E., Sol Hart, P., Maguire, L.A., Muter, B.A., 2009. Application of Risk Concepts to Wildlife Management: Special Issue Introduction. Hum. Dimens. Wildl. 14, 301–313. https://doi.org/10.1080/10871200903160944

Granovetter, M., 1983. The Strength of Weak Ties: A Network Theory Revisited. Sociol. Theory 1, 201–233. https://doi.org/10.2307/202051

Hassenforder, E., Ducrot, R., Ferrand, N., Barreteau, O., Anne Daniell, K., Pittock, J., 2016. Four challenges in selecting and implementing methods to monitor and evaluate participatory processes: Example from the Rwenzori region, Uganda. J. Environ. Manage. 180, 504–516. https://doi.org/10.1016/j.jenvman.2016.05.019

Hauck, J., Schmidt, J., Werner, A., 2016. Using social network analysis to identify key stakeholders in agricultural biodiversity governance and related land-use decisions at regional and local level. Ecol. Soc. 21. https://doi.org/10.5751/ES-08596-210249

Hauck, J., Stein, C., Schiffer, E., Vandewalle, M., 2015. Seeing the forest and the trees: Facilitating participatory network planning in environmental governance. Glob. Environ. Chang. 35, 400–410. https://doi.org/10.1016/J.GLOENVCHA.2015.09.022

Jasny, L., Waggle, J., Fisher, D.R., 2015. An empirical examination of echo chambers in US climate policy networks. Nat. Clim. Chang. https://doi.org/10.1038/NCLIMATE2666

Jochmans, K., Weidner, M., 2019. Fixed-Effect Regressions on Network Data. Econometrica 87, 1543–1560. https://doi.org/10.3982/ecta14605

Kocho-Schellenberg, J.-E., Berkes, F., 2015. Tracking the development of co-management: using network analysis in a case from the Canadian Arctic. Polar Rec. (Gr. Brit). 51, 422–431. https://doi.org/10.1017/S0032247414000436

Kochskämper, E., Challies, E., Newig, J., Jager, N.W., 2016. Participation for effective environmental governance? Evidence from Water Framework Directive implementation in Germany, Spain and the United Kingdom. J. Environ. Manage. 181, 737–748. https://doi.org/10.1016/j.jenvman.2016.08.007

Krackhardt, D., Nohria, N., Eccles, B., 2003. The strength of strong ties, in: Cross, R., Parker, A., Sasson, L. (Eds.), Networks in the Knowledge Economy. New York: Oxford University Press.

Lankester, A.J., 2013. Conceptual and operational understanding of learning for sustainability: A case study of the beef industry in north-eastern Australia. J. Environ. Manage. 119, 182–193. https://doi.org/10.1016/j.jenvman.2013.02.002

Lauer, F.I., Metcalf, A.L., Metcalf, E.C., Mohr, J.J., 2017. Public Engagement in Social-Ecological Systems Management: An Application of Social Justice Theory. https://doi.org/10.1080/08941920.2017.1364456

Leenders, R.T.A.J., 2002. Modeling social influence through network autocorrelation: constructing the weight matrix. Soc. Networks 24, 21–47. https://doi.org/10.1016/S0378-8733(01)00049-1

Lumosi, C.K., Pahl-Wostl, C., Scholz, G., 2019. Can "learning spaces" shape transboundary management processes? Evaluating emergent social learning processes in the Zambezi basin. Environ. Sci. Policy 97, 67–77. https://doi.org/10.1016/j.envsci.2019.04.005

Macgillivray, B.H., 2018. Beyond social capital: The norms, belief systems, and agency embedded in social networks shape resilience to climatic and geophysical hazards. Environ. Sci. Policy 89, 116–125. https://doi.org/10.1016/j.envsci.2018.07.014

Markowska, J., Szalińska, W., Dąbrowska, J., Brząkała, M., 2020. The concept of a participatory approach to water management on a reservoir in response to wicked problems. J. Environ. Manage. 259, 109626. https://doi.org/10.1016/j.jenvman.2019.109626

Marsden, P. V., Friedkin, N.E., 1993. Network Studies of Social Influence. Sociol. Methods Res. 22, 127–151. https://doi.org/10.1177/0049124193022001006

Masuda, N., 2007. Participation costs dismiss the advantage of heterogeneous networks in evolution of cooperation. Proc. R. Soc. B Biol. Sci. 274, 1815–1821. https://doi.org/10.1098/rspb.2007.0294

Matous, P., Todo, Y., 2015. Exploring dynamic mechanisms of learning networks for resource conservation. Ecol. Soc. 20, 36. https://doi.org/10.5751/ES-07602-200236

McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a Feather: Homophily in Social Networks. Annu. Rev. Sociol. 27, 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Miller Hesed, C.D., Van Dolah, E.R., Paolisso, M., 2020. Faith-based communities for rural coastal resilience: lessons from collaborative learning on the Chesapeake Bay. Clim. Change 1–21. https://doi.org/10.1007/s10584-019-02638-9

Mostert, E., Pahl-Wostl, C., Rees, Y., Searle, B., Tàbara, D., Tippett, J., 2007. Social learning in European river-basin management: barriers and fostering mechanisms from 10 river basins. Ecol. Soc. 12.

Muter, B.A., Gore, M.L., Riley, S.J., 2013. Social Contagion of Risk Perceptions in Environmental Management Networks. Risk Anal. 33, 1489–1499. https://doi.org/10.1111/j.1539-6924.2012.01936.x

Paolisso, M., Prell, C., Johnson, K.J., Needelman, B., Khan, I.M.P., Hubacek, K., 2019. Enhancing socio-ecological resilience in coastal regions through collaborative science, knowledge exchange and social networks: a case study of the Deal Island Peninsula, USA. Socio-Ecological Pract. Res. 1, 109–123. https://doi.org/10.1007/s42532-019-00010-w

Pasquier, U., Few, R., Goulden, M.C., Hooton, S., He, Y., Hiscock, K.M., 2020. “We can’t do it on our own!”—Integrating stakeholder and scientific knowledge of future flood risk to inform climate change adaptation planning in a coastal region. Environ. Sci. Policy 103, 50–57. https://doi.org/10.1016/j.envsci.2019.10.016

Plummer, R., Baird, J., Dzyundzyak, A., Armitage, D., Bodin, Ö., Schultz, L., 2017a. Is Adaptive Co-management Delivering? Examining Relationships Between Collaboration, Learning and Outcomes in UNESCO Biosphere Reserves. Ecol. Econ. 140, 79–88. https://doi.org/10.1016/j.ecolecon.2017.04.028

Plummer, R., Dzyundzyak, A., Baird, J., Bodin, Ö., Armitage, D., Schultz, L., 2017b. How do environmental governance processes shape evaluation of outcomes by stakeholders? A causal pathways approach. PLoS One 12, e0185375. https://doi.org/10.1371/journal.pone.0185375

Prell, C., Hubacek, K., Quinn, C., Reed, M., 2008. “Who’s in the network?” When stakeholders influence data analysis. Syst. Pract. Action Res. 21, 443–458. https://doi.org/10.1007/s11213-008-9105-9

Prell, C., Hubacek, K., Reed, M., 2009. Stakeholder Analysis and Social Network Analysis in Natural Resource Management. Soc. Nat. Resour. 22, 501–518.

Prell, C., Lo, Y.J., 2016. Network formation and knowledge gains. J. Math. Sociol. 40, 21–52. https://doi.org/10.1080/0022250X.2015.1112385

Prell, C., Reed, M., Hubacek, K., 2011. Social network analysis for stakeholder selection and the links to social learning and adaptive co-management, in: Bodin, Ö., Prell, C. (Eds.), Social Networks and Natural Resource Management: Uncovering the Social Fabric of Environmental Governance. Cambridge University Press, Cambridge, UK, pp. 95–118.

Prell, C., Reed, M.S., Racin, L., Hubacek, K., 2010. Competing structure, competing views: The role of formal and informal social structures in sahping stakeholder perceptions. Ecol. Soc. 15, 34.

Rathwell, K.J., Armitage, D., Berkes, F., 2015. Bridging knowledge systems to enhance governance of environmental commons: A typology of settings. Int. J. Commons 9, 851. https://doi.org/10.18352/ijc.584

Reed, M.S., 2008. Stakeholder participation for environmental management: A literature review. https://doi.org/10.1016/j.biocon.2008.07.014

Reed, M.S., Evely, A.C., Cundill, G., Fazey, I., Glass, J., Laing, A., Newig, J., Parrish, B., Prell, C., Raymond, C., Stringer, L.C., 2010. What is Social Learning? Ecol. Soc. 15.

Rist, S., Chiddambaranathan, M., Escobar, C., Wiesmann, U., 2006. “It was hard to come to mutual understanding...”-The multidimensionality of social learning processes concerned with sustainable natural resource use in India, Africa and Latin America. Syst. Pract. Action Res. 19, 219–237. https://doi.org/10.1007/s11213-006-9014-8

Sandström, A., Crona, B., Bodin, Ö., 2014. Legitimacy in Co-Management: The Impact of Preexisting Structures, Social Networks and Governance Strategies. Environ. Policy Gov. 24, 60–76. https://doi.org/10.1002/eet.1633

Scherer, C.W., Cho, H., 2003. A Social Network Contagion Theory of Risk Perception. Risk Anal. 23, 261–267. https://doi.org/10.1111/1539-6924.00306

Schiffer, E., Hauck, J., 2010. Net-Map: Collecting Social Network Data and Facilitating Network Learning through Participatory Influence Network Mapping. Field methods 22, 231–249. https://doi.org/10.1177/1525822X10374798

Schwilch, G., Bachmann, F., Valente, S., Coelho, C., Moreira, J., Laouina, A., Chaker, M., Aderghal, M., Santos, P., Reed, M.S., 2012. A structured multi-stakeholder learning process for Sustainable Land Management. J. Environ. Manage. 107, 52–63. https://doi.org/10.1016/j.jenvman.2012.04.023

Shackleton, R.T., Adriaens, T., Brundu, G., Dehnen-Schmutz, K., Estévez, R.A., Fried, J., Larson, B.M.H., Liu, S., Marchante, E., Marchante, H., Moshobane, M.C., Novoa, A., Reed, M., Richardson, D.M., 2019. Stakeholder engagement in the study and management of invasive alien species. J. Environ. Manage. 229, 88–101. https://doi.org/10.1016/j.jenvman.2018.04.044

Stadtfeld, C., Snijders, T.A.B., Steglich, C., van Duijn, M., 2018. Statistical Power in Longitudinal Network Studies. Sociol. Methods Res. https://doi.org/10.1177/0049124118769113

Teodoro, J.D., Nairn, B., 2020. Understanding the Knowledge and Data Landscape of Climate Change Impacts and Adaptation in the Chesapeake Bay Region: A Systematic Review. Climate 8, 58. https://doi.org/10.3390/cli8040058

Therrien, M.-C., Jutras, M., Usher, S., 2018. Including quality in Social network analysis to foster dialogue in urban resilience and adaptation policies. https://doi.org/10.1016/j.envsci.2018.11.016

Uzzi, B., Lancaster, R., 2003. Relational Embeddedness and Learning: The Case of Bank Loan Managers and Their Clients. Manage. Sci. 49, 383. https://doi.org/10.1287/mnsc.49.4.383.14427

van Aalst, M.K., Cannon, T., Burton, I., 2008. Community level adaptation to climate change: The potential role of participatory community risk assessment. Glob. Environ. Chang. 18, 165–179. https://doi.org/10.1016/j.gloenvcha.2007.06.002

van der Wal, M., De Kraker, J., Offermans, A., Kroeze, C., Kirschner, P.A., van Ittersum, M., 2014. Measuring Social Learning in Participatory Approaches to Natural Resource Management. Environ. Policy Gov. 24, 1–15. https://doi.org/10.1002/eet.1627

Weenig, M.W.H., Midden, C.J.H., 1991. Communication network influences on information diffusion and persuasion. J. Pers. Soc. Psychol. 61, 734–742. https://doi.org/10.1037/0022-3514.61.5.734