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Learning to understand: disentangling the outcomes of stakeholder participation in climate change governance

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ABSTRACT

Stakeholder participation is increasingly seen as beneficial for short and long term responses to climate change risks. Past research highlights the role social networks play as both a key outcome of participation, as well as an important step towards other environmental governance goals. This paper focuses on the social relation of *mutual understanding*, which is often discussed in the environmental governance literature, but has yet to be studied as an empirical social network in its own right. Our paper builds and tests a conceptual framework linking participation to mutual understanding and social learning. We analyze three waves of network and perceptions data gathered on stakeholders participating in the Integrated Coastal Resiliency Assessment (ICRA) project, a 2.5 year-long project aimed at developing a collaborative research assessment on the vulnerabilities to climate change experienced by an island community located in the Chesapeake Bay, USA. Our findings suggest that participation (measured as co-attendance in project events) leads to the formation of mutual understanding ties among stakeholders, but these ties do not necessarily lead to more similarity in stakeholders' perceptions on climate change. We reflect on these findings, and the project more broadly, noting that our study lends support to scholars arguing that feelings of mutual understanding are potentially more important for certain forms of collective action, as opposed to whether or not stakeholders increase their shared beliefs or perceptions about the environmental problem in question.

1. Introduction

Stakeholder participation is increasingly seen as a valuable strategy for developing short and long term adaptation responses to climate change risks (Barrutia and Echebarria, 2019; Galappaththi et al., 2019; Sautier et al., 2017). The environmental governance literature highlights the role of stakeholder participation as facilitating learning and collective action (Armitage et al., 2008; Cundill and Rodela, 2012; Daniels and Walker, 2001; Plummer et al., 2012; Reed et al., 2010), and achieving sustainable solutions for a range of environmental problems (de Vente et al., 2016; Lauer et al., 2017; Pahl-Wostl et al., 2007). Social networks are situated as an important part of participatory processes (Bodin, 2017; Jasny et al., 2021; Plummer et al., 2017; Sayles and Baggio, 2017), as the ties formed among stakeholders enable knowledge exchanges and understanding to arise, leading to learning and/or collective action (Lankester, 2013; Matous and Todo, 2015; Rathwell et al., 2015; Sandström et al., 2014; Schwilch et al., 2012; Teodoro et al., 2021). Although such work supports the general argument that social networks are important for environmental governance (Bodin, 2017; Bodin and Crona, 2008; Bodin and Prell, 2011), several questions remain unanswered regarding the underlying social processes that link participation to tie formation, and from tie formation to learning and other outcomes (Cundill and Rodela, 2012). For example, a number of studies on social learning identify various *kinds* of relations, such as trust, respect, communication, collaboration, or understanding (Armitage et al., 2008; Bodin, 2017; Daniels and Walker, 1996; Plummer et al., 2017; Prell et al., 2009, 2011; Reed et al., 2010; Rist et al., 2006; Schusler et al., 2003; Trimble and Berkes, 2013), yet quantitative measures of these different kinds of networks have not been widely discussed or developed, nor have they been systematically tested in relation to stakeholder participation and/or social learning (see Teodoro et al., 2021 as an exception). As such, it remains unclear how a number of these relatons and processes are linked together, and whether some are more relevant/significant than others.

In this study, we use a network approach to build and test a conceptual framework for a participatory project, which was aimed at (i)

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building a shared understanding of the drivers and impacts related to climate change (CC) and (ii) generating a collaborative research report on the CC vulnerabilities and resiliencies of a particular geographical area in the USA. This project, entitled the Integrated Coastal Resiliency Assessment (ICRA), was a transdisciplinary project that took place on the Deal Island Peninsula (DIP), in the Chesapeake Bay, Maryland, USA, over the course of 2.5 years (between 2016 and 2018). This area has increasingly experienced CC related impacts, such as sea-level rise, increased storms and flooding (Teodoro and Nairn, 2020), and these impacts are progressively being felt by locals living in the area and/or engaged in fisheries-based activities (Paolisso et al., 2019). At the outset of the ICRA, longitudinal network analysis was employed to capture the extent to which mutual understanding ties emerged among participants, as well as whether such understanding co-evolved with changes in participants' CC perceptions. By the end of the project, anthropologists on the team had gathered three waves of network data via an online survey on stakeholders' feelings of understanding of others' views regarding socio-environmental changes impacting the DIP. The online survey also contained questionnaire items measuring stakeholders' CC perceptions. These perception measures, moreover, were developed inductively by anthropologists on the team who had been working in the DIP area for a number of years (Paolisso et al., 2019; Van Dolah, 2018), and hence reflected views heard in the field prior to the ICRA launch. Before offering further details on the study design, we present our conceptual framework linking participation to mutual understanding and social learning.

2. Conceptual framework: Participation, mutual understanding and learning

Over the past two decades, the environmental governance literature has increasingly put forth the argument that the learning occurring in participatory processes among diverse stakeholders leads to better governance outcomes (Armitage et al., 2008; Daniels and Walker, 2001, 1996; Pahl-Wostl et al., 2007; Plummer et al., 2017). By engaging a diverse set of stakeholders in an iterative dialog, participants form bonds of understanding that lead to ongoing, mutual learning, thus potentially leading to shifts in cognitions and perspectives at multiple levels (Daniels and Walker, 2001, 1996; Garmendia and Stagl, 2010; Reed et al., 2018; Walker and Daniels, 2019).

In this paper, we focus on the social relation of *mutual understanding* as it arises in the context of participatory processes, and consider how it contributes to shifting participants' views of climate change over time (Daniels and Walker, 2001, 1996; Walker, 2007). Mutual understanding refers to stakeholders feeling that their views, values, and opinions are heard and understood by other participants (and vice versa). Such understanding does not necessarily reflect greater amounts of agreement among stakeholders (Armitage et al., 2008; Daniels and Walker, 1996; Paolisso et al., 2019), but it is often seen as a necessary, intermediate step for deeper forms of learning to arise, and for the development of a shared understanding across the network as a whole (Daniels and Walker, 2001; Pahl-Wostl et al., 2007; Rist et al., 2006;.). When two stakeholders share a bond of understanding, they are more open to learning from one another (Daniels and Walker, 2001, 1996), and also more likely to reflect on their own individual attitudes, thus potentially leading to a shift in their perceptions that aligns with others and/or environmental goals (de Vente et al., 2016; Fazey et al., 2006; Rist et al., 2006). Such a process, moreover, stands in contrast to 'knowledge transfer' scenarios, in which experts educate the public in a hierarchical, top-down fashion regarding environmental problems and solutions (Daniels and Walker, 1996; Reed et al., 2010; Walker, 2007), and which the problems discussed are often devoid of the insights, values and opinions of local stakeholders, and/or the public at large (Daniels and Walker, 2001, 1996; Reed et al., 2010; Walker, 2007). Some evidence suggests that shifting the attitudes of stakeholders requires the development of mutual understanding, as an intermediary step, in order to encourage an overall openness to learning and reflective thinking (Daniels and Walker, 1996; Rist et al., 2006). Yet as of this writing, we have not yet seen a study that systematically tests the links between participation, mutual understanding, and learning in the way we describe here.

Past network studies on participation and environmental governance emphasize relations based on collaboration, communication, and advice and how the presence of such ties (and their patterns) correlate with positive governance outcomes (see Bodin, 2017 and Jasny et al., 2021 for reviews). We build on this past research by calling attention to the social relation of mutual understanding, which though highlighted in the social learning and environmental governance literature, has yet to be studied as an empirical social network in its own right. These conceptual models of mutual understanding, as it arises from participation and influences learning, is summarized in Fig. 1 below.

In the next sections, we unpack Fig. 1 according to the specified hypotheses.

2.1. *Stakeholder participation (co-attendance) leads to mutual understanding ties*

Past research supports the idea that participation enables diverse, heterogeneous stakeholders to share their opinions and beliefs about environmental issues (Daniels and Walker, 2001; Ernoul and Wardell-Johnson, 2013; Lumosi et al., 2019; Paolisso et al., 2019; Rist et al., 2006), which in turn facilitates mutual understanding among participants (Hegger and Dieperink, 2014; Mostert et al., 2007; Rist et al., 2006). Here, the goal is *less* about stakeholders arriving at a similar set of opinions, and *more* about enabling a culture of openness and understanding (Daniels and Walker, 2001, 1996) so that a shared view of the complexity of the problem arises, in spite (or because) of participants' diverse views and beliefs. If done successfully, stakeholder participation leads to increased feelings of being both heard and understood among participations (Lumosi et al., 2019; Mostert et al., 2007; Paolisso et al., 2019; Reed et al., 2010; Rist et al., 2006; Schwilch et al., 2012), regardless of whether participants agree on the fundamental nature of the problem or solution (Armitage et al., 2008; Ostrom, 2010; Tompkins and Adger, 2004; Walker and Daniels, 2019). In this line of reasoning, stakeholders that co-attend the same participatory process may develop mutual understanding ties; participation, leading to H1 below:

H1: Participation (co-attendance) leads to mutual understanding among stakeholders.

2.2. *Mutual understanding and social learning*

Other literature posits that the social networks arising from participatory processes are a necessary, intermediate condition enabling individuals to learn from one another, and shift their position or views to be more in alignment with one another and the overall governance question (Crona et al., 2011; Cundill and Rodela, 2012; Garmendia and Stagl, 2010; Lankester, 2013; Sandström et al., 2014; Schwilch et al., 2012; van der Wal et al., 2014). Here, the formation of bonds based on mutual understanding provides the channels through which participants may influence one another (Crona et al., 2011; Daniels and Walker, 1996; Muter et al., 2013; Rist et al., 2006; Sandström et al., 2014; Schwilch et al., 2012). This leads to H2 below:

H2: Participation (co-attendance) leads to mutual understanding ties, which in turn leads to social learning (i.e., similarity in CC views).

2.3. *The role of homophily*

Working against the aim of participation to build cohesion across diverse stakeholders is an inherent social tendency characterizing many empirical networks. Homophily, a well-documented phenomenon within the social networks literature, describes the tendency of

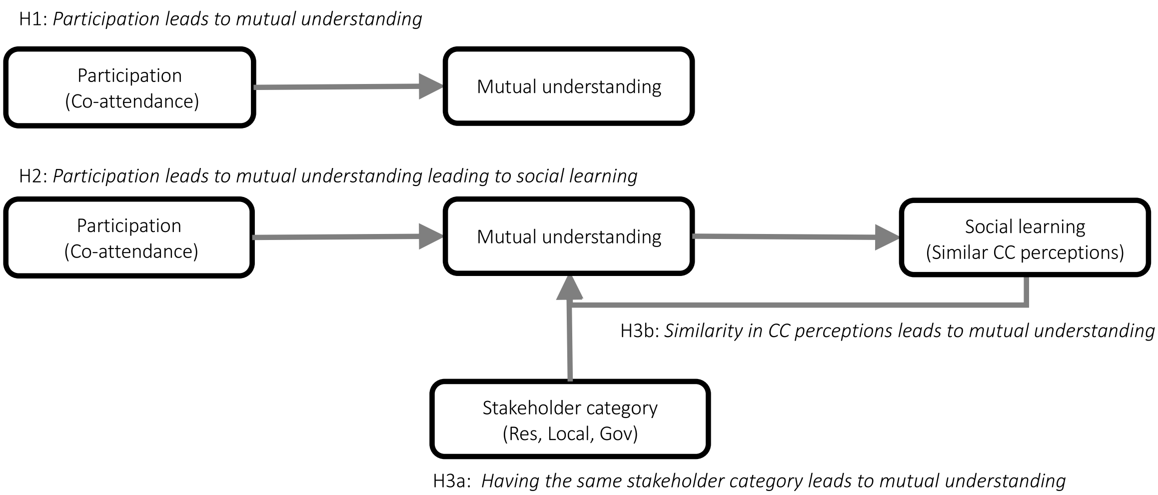


Fig. 1. Conceptual framework.

individuals to prefer the presence of similar others (McPherson et al., 2001). Here, a distinction is made between *status homophily*, i.e. homophily among those with same/similar characteristics, such as age, sex, or education, and *value homophily*, i.e. similarity in values, perceptions, beliefs and thinking (Lazarsfeld and Merton, 1954). In the case of the ICRA, there are reasons to believe that both forms of homophily may be present. With regards to status homophily, past research on the DIP indicates that local residents tend to be close-knit, self-sufficient, and shying away from formal governance and scientific expertize (Johnson, 2014). Thus, a competing tendency working against ICRA goals may be that mutual understanding is more likely to form among similar stakeholders (i.e., locals, researcher, or government) throughout the duration of the project

H3a: Having the same stakeholder category leads to mutual understanding.

In addition, value homophily might be present in our network via the formation of mutual ties of understanding among those with similar CC perceptions. As stakeholders interact over time, and voice and hear others' views with regards to climate change and the DIP, they may acquire insights into others that share similar views as themselves, and consequently, begin seeing such others as more understanding. Such a value- (or rather perception) based form of homophily, moreover, may very well arise towards the end of the project, after stakeholders have had sufficient time to interact, learn from and about each other's views regarding the DIP and climate change:

H3b: Similarity in climate change perceptions leads to mutual understanding.

In the following section, we describe how we test this conceptual model through longitudinal network analysis on a stakeholder network in the Deal Island Peninsula, Maryland, USA.

3. Materials and methods

Network data and CC perception data were collected at three time periods between 2016 and 2018. The first wave of data were collected after only two participatory events occurred. The second wave of data were collected after a total of 11 events occurred, and the final wave of data were gathered after a total of 14 events occurred. Participatory activities included meetings and workshops geared toward encouraging open discussion around issues of flooding, coastal erosion, conservation and restoration of marshes and possible actions that may address those issues (Johnson et al., 2017). The stakeholder network (n = 60) consisted of a diverse range of stakeholders including resource managers from state and local governments (n = 21), a multidisciplinary group of scientists based in the region (n = 23), and local community residents (n = 16). These stakeholders, moreover, were largely targeted by project leaders as a means to capture diversity in viewpoints. The stakeholders in the final analysis can also be understood as active participants, i.e., stakeholders who regularly attended ICRA activities (Prell et al., 2021) and, in general, engaged in the ICRA project aims.

To measure the network of *mutual understanding*, we used a roster including all ICRA participants' names, and asked respondents to rate each ICRA participant via the following statement: "I feel that this person understands my views regarding the DIP area." This measure was developed to reflect the literature on collaborative learning, which discusses participatory processes as leading to feelings of being understood among participants (Daniels and Walker, 2001). This question was part of our survey that was implemented three times over the course of the study, resulting in three rounds of network data.

The answers to this question ranged from 1 ('a little') to 2 ("somewhat") to a maximum of 3 ("a lot"). These data thus resulted in a valued, actor by actor matrix, which we dichotomized, such that responses of 2 or 3 were given a value of 1, and 0 otherwise. Thus, we focused on medium-to-strong feelings of being understood, as stronger relations tend to provide better/more reliable information on tie presence than weak ones (Marsden, 1990), and in our case, provide a stronger indicator for formation of mutual understanding ties. Next, we symmetrized the data so that only ties that were reciprocated were included in the final dataset, i.e. unreciprocated ties were omitted. As such, a mutual tie in this dataset reflects actor i stating they feel understood by j and vice versa. The three matrices that resulted from the three rounds of data collection, and the transformations to these matrices described above, thus composed our dependent network variable.

To measure *stakeholder participation*, we converted the attendance sheets for all ICRA meetings into bipartite matrices, in which columns contained ICRA meeting events, rows contained names of all ICRA participants, and cells contained a 1 if a given actor attended a given event, and 0 otherwise. The first bipartite matrix held data on stakeholders' ICRA attendance for events occurring between the first and second wave of survey data gathering (total of 9 events), and a second matrix held attendance data for events occurring between the second and third wave of survey data gathering (total of 3 events). These bipartite matrices were then converted to valued, one-mode networks, representing stakeholders' co-attendance. Here, cell numbers represented the total number of meetings co-attended by any given pair of stakeholders. These valued, one-mode projections of the attendance bipartite data were then modeled as *dyadic covariates* in our model for predicting the formation of mutual understanding ties.

Data on *stakeholders' categories* (local resident, researcher, or government employee) was determined based on stakeholder's primary relationship to the DIP. In most cases, this was straightforward, as participants were typically targeted and invited to the ICRA on the basis on their stakeholder category. There were 2 cases in which a stakeholder identified with more than one category, e.g. the person both lived on the DIP and researched the DIP. In these two instances, the person was asked to choose the category they most identified with in relation to their participation in the ICRA project. These stakeholder categorical data were treated as *covariates* in our model for predicting mutual tie formation.

Data on *stakeholder CC perceptions* were gathered via seven 4-point Likert statements (Table 1). These questions were inductively derived by anthropologists on the team who had been researching the DIP area prior to the project's launch (Johnson et al., 2018). As such, these statements reflected CC perceptions that anthropologists had heard in their qualitative field work. Participants were asked to rate the statements depending on how much they agreed or disagreed with each statement. The responses had high internal reliability (Cronbach $\alpha = 0.96$) and were combined into a single averaged score in the following way: we took the average of the 7 Likert scale responses. Given that Likert scales are ordinal in nature, the average score was converted into ordinal data (i.e., integers) by superimposing an amplified 5 point ordinal scale on the range of the averaged scores. By subdividing the space into 5 'bins' and not 4, we intended to conserve the data of the scores' decimals. Ultimately, the integers used in the SIENA models as variable inputs were the ordinal values from 1 to 5, representing an amplified scale of the averaged scores. For example, the scores between 1.5 (min) and 2.0 were transformed to a 1; scores between 2.0 and 2.5 were transformed to 2, and so on up to scores higher than 3.5 were transformed to a 5. These CC perceptions data composed an *attribute dependent variable* for our model.

The covariates and dependent variables were brought together in a modeling environment designed for longitudinal network data analysis. The stochastic actor-oriented models, or SAOMs (Snijders et al., 2010; Steglich et al., 2010), are a probabilistic modeling environment designed for teasing apart co-evolutionary tendencies pertaining to network formation and changing actor attributes (in our case, such attributes are CC perceptions). The intuition behind SAOMs is that actors evaluate their position in the network structure, and make changes to ties or attributes based on a probabilistic evaluation of network choices, which in turn are informed by model specifications (e.g., whether to reciprocate a tie or not). One model (the network selection model) accounts for changes in networks by considering endogenous tendencies (e.g., the general tendency for closed triads), as well as exogenous ones involving actor attributes (e.g., the likelihood of mutual tie forming between *local* stakeholders). A second model (the attribute model) handles the impacts of network patterns on actor attributes (e.g., climate change perceptions), such as whether one's perceptions become more similar over time to one's networked alters. These two models are estimated simultaneously, so that changes in the network model can affect changes in the attribute model (and vice versa), leading to results that disentangle these two processes, while controlling for competing network tendencies. In addition, estimation of these network and attribute models occurs from the view point of individual actors, and thus model results represent probabilistic tendencies organized around the individual actor (and not necessarily reflective of a hard assumption that actors are consciously intentional in their choices, see Ripley et al., 2019).

Table 1
Climate change perceptions statements (Cronbach alpha = 0.96).

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 can help communities cope with climate change.

In more recent years, SAOMs have been extended to capture network dynamics of undirected networks, or mutual ties (Snijders and Pickup, 2017). The reasoning behind these extensions is informed, in part, on the pairwise assumptions found in utility models of network evolution (e.g., Jackson and Wolinsky, 1996). Here, two actors form a tie when both find doing so is beneficial. In the context of SAOMs, one can specify the estimation process such that an actor, at a given (micro)step in the estimation process, is given the opportunity to propose the formation of a new tie, to which confirmation by the other actor is needed prior to the tie being formed (Mercken et al., 2009; Ripley et al., 2019). Both actors' decisions to form the tie are based on each one's (probabilistic) evaluation of possible network choices. In the ICRA context, a tie of *mutual understanding* can thus only arise in the estimation process when both stakeholders confirm the other as understanding. Although studies are starting to emerge that apply SAOMs to mutual tie formation (Manger et al., 2012; Snijders and Pickup, 2016), we are unaware of any study that has applied SAOMs to a *mutual cognitive relation* such as understanding in the way we do so here, even though networks based on cognition, beliefs, or affection are well documented in the wider network analysis literature (Borgatti et al., 2009).

For our purposes, we used SAOMs to capture the co-evolutionary tendencies depicted in Fig. 1. Towards those ends, we introduced the one-mode, symmetrical network of *mutual understanding* as a dependent network variable; *climate change perceptions* as a dependent attribute variable; *stakeholder category* as a constant covariate; and the 2 *co-attendance matrices* as constant dyadic covariates (as the three waves of data were modeled as two separate periods, see below). For testing H1, we used the *dyadic covariate (X)* effect in the network selection model, where a positive value captures the tendency of actors who co-attend the same ICRA events to then form *mutual understanding* ties. For H2, we again made use of the *dyadic covariate (X)* effect in the selection model, and in addition, we used the *total similarity (totSim)* effect in the attribute model, the later effect capturing, when the resulting value is positive, the tendency of actors to be similar to their alters, and where the total influence of these alters is proportional to the number of alters for a given ego. For H3a, we used the *same covariate (sameX)* effect in the network selection model, where a positive value reflects tendencies to form mutual understanding ties with others of the same stakeholder category, and for H3b, we included the *covariate similarity (simX)* effect, where a positive value captures the tendency for ego to form mutual understanding ties with those having similar climate change perceptions identity.

As the *sameX* and *simX* effects are composed of lower-order configurations, in particular, the *egoX* effect, we included the *egoX* for *CC perceptions* and also for *local* and *research* stakeholder categories. A positive value for the *egoX* effect indicates tendencies for stakeholders scoring high on a given attribute (e.g. CC perceptions) to form mutual understanding ties. In relation to the stakeholder categories, we ran preliminary score-type tests for the *egoX* effect to ascertain which categories to include in our model. The score-type test enables one to test a parameter without estimating it, and is a useful strategy to use in cases where there are many parameters to consider for the given information in a dataset (Ripley et al., 2019). As our dataset is rather small (n = 60), this put constraints/limits on the number of effects to include in our models, and as the *egoX* effect was included more as an underlying control for the hypothesized tendencies of homophily, using the score-type tests in this fashion enabled us to ascertain which of these lower-order effects was necessary for model convergence. This resulted in the inclusion of the *egoX* effect for locals and researchers.

Network endogenous effects were also included in our network selection model to control for the interdependencies and underlying tendencies across the mutual understanding network. These include the *degree effect*, where a positive parameter indicates a general tendency for forming mutual ties, and the transitive *gwesp effect*, where a positive value indicates clustering at the local level, more particularly, the tendency for actors to form mutual ties, such that, given a mutual tie from actor i to h, and from h to j, then there is a strong likelihood of actor i and j to form a mutual tie as well. Transitivity is a widely held phenomenon characterizing a variety of networks, and is often considered a natural 'bias' of networks in general (Skvoretz et al., 2004). With regards to a network composed of mutual understanding ties, transitivity takes the form of a closed triad structure, as all ties are symmetric. Recent studies show support for transitivity in perception-based relations (Daniel et al., 2018), and in the case of the ICRA, one would expect such triadic closure, based on mutual understanding, to arise as part of the intended aim of the project leaders to increase the overall understanding across the network as a whole. Said differently, in participatory settings, where ongoing interactions and dialogs occur among the same group of participants, mutual understanding can be expected to grow from simple pairings of stakeholders to the network as a whole (Daniels and Walker, 2001, 1996) leading to feelings of group coherence (Hajer, 1997). As such, the presence of closed triads in such a setting is indicative of mutual understanding *moving* beyond the dyad to larger subgroupings, as triads are, in general, considered an important building block of network density as a whole (Robins et al., 2005). In participatory settings, actors may help one another, over time, to not only understand their own views regarding governance scenarios, but the views of others. Here, the understanding existing between a given actor i and j and between j and k may lead to i and k to likewise understand one another, either because j has helped in this process, or because both i and k trust the opinions and views of j.

Additionally, SAOMs include default *rate effects* for both the network and behavioral models. For the network selection model, the rate effect indicates the extent to which actors have opportunities to change their ties; and for the attribute model, the rate effect controls for the opportunities to change CC perception values from one wave to the next. The *linear shape effect* measures the overall tendency toward high or low CC perception values, where a negative value indicates that the majority of actors scored below the CC perception mean, and a positive value indicates the opposite. The *quadratic shape effect* controls the effect of a stakeholder's CC value on itself, where a negative value implies the tendency of the perceptions to decrease over time (when the value was originally high), and a positive value indicating the tendency for perception scores to increase towards the high end of the scale (Snijders et al., 2010). A full list of effects are displayed, with accompanying formulas, in Table 2.

Finally, as the amount of attendance in ICRA meetings varied from one period to the next, we made the choice to run two separate models, and in this way controlled for the time heterogeneity inherent in the data. When working with two or more periods, i.e., three or more waves, there is a concern regarding whether parameters resulting in a SAOM are constant across the periods. If there is a great amount of change in the network between two consecutive observations, this can result in biased inferences (Lospinoso et al., 2011; Ripley et al., 2019). One means of handling this is to model the periods separately, so that the modeled amount of change in one period does not impact that of the other.

4. Results

4.1. Descriptive results

Descriptive characteristics of the attendance and understanding networks at the three time points are found in Table 3.

The amount of changes between the 3 measurement moments for mutual understanding ties was expressed by a Jaccard coefficient of 0.250 and 0.273 between period 1 (wave 1 and 2) and period 2 (wave 2 and 3), respectively, for the mutual understanding network. This coefficient expresses the amount of change between two consecutive waves within a range from 0 to 1 (with 1 representing no change). These coefficient values lie within the normal, suggested range for using SAOMs (Ripley et al., 2019). Network characteristics for every data period is found in Table 3, including number of observed ties and overall density for each network. We note that for the co-attendance network, only the

Table 2
List of effects included in Siena models. SAOM effects included in the modeling framework.

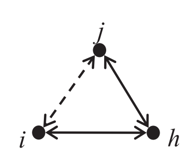
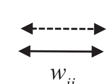
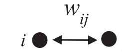
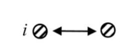
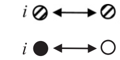
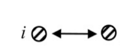
Effect name	Underlying tendency	Mathematical formula	Graphical representation
Endogenous network effects			
Rate	The speed by which each network actor gets an opportunity for changing her score on the dependent variable	$\gamma_{i1}^{net} = \rho_m^{net}$	
Degree	The basic tendency to create and maintain ties	$\sum_j x_{ij}$	
Transitive gwesp	Tendency for actors to form mutual ties, such that, given a mutual tie from actor i to h, and from j to h, there is a strong likelihood of actor i and j to form a mutual tie as well.	$\sum_{k=1}^{n-2} e^{\alpha}\left(1-\left(1-e^{-\alpha}\right)^{k}\right) EPFF_{ik}$	
Network formation effects			
Dyadic covariate (X effect)	The extent to which i and j both attending same events (w) promotes the creation or maintenance of a mutual understanding tie (H1)	$\sum_j x_{ij}(w_{ij} - \bar{w})$	
Covariate same (sameX effect)	Tendency for mutual ties to form among stakeholders with the same covariate (stakeholder identity) value (H3a)	$\sum_j x_{ij} I\{v_i = v_j\}$	
Covariate similarity (simX effect)	Tendency to form mutual ties with stakeholders that have similar covariate (CC perception) values (H3b)	$\sum_j x_{ij}\left(sim_{ij}^{v} - \widehat{sim^{v}}\right)$	
Covariate ego (egoX effect)	Tendency of an actor with a certain covariate value to form ties	$v_i x_i +$	
Perception change effects			
Rate	Tendency of actors to increase their perception score by 1 or stay the same, for each period.	$\gamma_i^{beh} = \rho_m^{beh}$	
Linear; quadratic shape	Linear shape measures the overall tendency toward high or low CC perception values; and *quadratic shape controls* the effect of a CC perception value on itself	$z_i; z_i^2$	
Total similarity in perceptions (tot*Sim* effect)	Tendency for adopting similar CC perceptions of one's alters, where the total influence of alters is proportional to the number of alters (H2)	$\sum_j x_{ij}\left(sim_{ij}^{z} - \widehat{sim^{z}}\right)$	

Table 3
Descriptive statistics of networks.

	Wave 1		Jaccard (1→2)	Wave 2		Jaccard (2 →3)	Wave 3	
	Ties	Density		Ties	Density		Ties	Density
Mutual Understanding (DV)	198	0.11	0.250	312	0.11	0.273	322	0.12
Co-attendance (Covariate)	–	–	–	512	0.15	–	348	0.10

ties and densities were calculated for waves 2 and 3, given that these networks operated as constant covariates for period 1 and 2, respectively.

Based on descriptive statistics, it is noticeable that the mutual understanding network is growing over time; increasing in the number of ties and density. Stakeholder attributes, namely the individual scores of climate change perceptions (range 1 – 5) for each wave are described in Table 4.

In looking at the average CC perception scores, across the three waves, we note a slight decrease in the mean value for CC perceptions, and a slight increase in the SD. The difference scores for each period were computed, and their frequency counts are also shown in Table 4. On the whole, most stakeholders, in both periods, maintained their perception scores. In period 1, five stakeholders decreased their scores, and four increased their scores. In period 2, three have decreased their scores, whereas two increased them, with one of these two increasing their score by 3 values. We will return to this point later in the article (see Discussion section below).

4.2. Results from longitudinal analysis

Tables 5 and 6 show model results for period 1 and period 2, respectively. We note that the same network effects were used for both periods to ensure that the same tendencies were modeled consistently across both periods. In addition, both sets of models were generated in a step-wise fashion in order to first highlight hypothesized tendencies, before building more complex models with competing network effects. Before discussing individual model results, we first start by noting some general patterns across all models found in Tables 5 and 6. In the selection models for both periods, the default *rate parameter* indicates actors changing their ties at a similar rate for both periods for the mutual understanding network. For the attribute models, the *rate* parameter for CC perceptions shows a tendency of individuals to change their perceptions at similar degrees in both periods. In addition, the *linear* shape holds a positive, weakly significant coefficient (with the p-value less than 0.1) and the results for the *quadratic* term are non-significant. Thus, there is a weak, upward trend in perception scores, and this trend seems guided by a few individual actors increasing their perceptions scores in Period 2. This is shown in the frequency counts for difference scores found in Table 4: most actors remain the same, and a few change their scores, with one actor in period 2 increasing their score by 3 points.

Endogenous effects included for all models include the *degree* and transitive *gwesp* effects. The negative, significant coefficient for the *degree* effect, across all models, indicates a tendency away from forming higher numbers of ties, unless other specified effects such as transitivity are included in the model. The transitive *gwesp* effect for mutual understanding shows a positive, significant coefficient, across all models, indicating the tendency for forming mutual ties that lead to closed triads across both periods. The positive effect on transitivity indicates that an actor who holds strong mutual understanding ties with two other actors (i.e., open triad) will likely result in those two actors developing strong mutual understanding ties between them (i.e., closed triad). Looking beyond the clustering tendency expected from empirical networks, transitivity in a mutual understanding network shows that understanding among these stakeholders emerges in a deeply personal way: actor *i* has a reciprocal understanding tie with actor *j* and *k* (i.e., knowing enough about the others' views while displaying understanding). Thus, actors *j* and *k* are more likely to develop a mutual understanding tie between them (i.e., displaying understanding between them similar to that between each of them and actor *i*).

Turning to the individual model results, Model 1a and 1b test for H1 across both periods. The positive, significant coefficient for the *dyadic covariate (X) effect* indicates that actors that attend the same events tend to form mutual understanding ties with one another, and this finding, moreover is replicated in all subsequent models across both periods, and thus, indicates strong support for H1, even when controlling for a number of competing tendencies. As such, support is found for H1. Model 2a and 2b test for H2 using the *total similarity effect*. Here, the results show no significant findings for this effect, i.e. there is no support for the idea that actors that mutually understand one another share similar CC perceptions, and hence, H2 is not supported.

Model 3a/b tests for homophily tendencies among stakeholders that think similarly about CC, using the *similar covariate effect*, as well as among stakeholders of the same type for mutual understanding ties using the *same covariate effect*, as well as homophily. Beginning with CC perceptions, neither period 1 nor period 2 show any strong tendencies for stakeholders, over time, to form mutual understanding ties with those who think similarly about climate change. Hence, H3b is not supported. However, in considering homophily among stakeholders of the same category, Models 3a/b and Models 4a/b show an interesting set of patterns. First, the tendency for local stakeholders to form mutual understanding ties with each other is confirmed in both periods. This implies that, even with a number of participatory events across 2.5 years, the strong tendency of locals feeling understood by other locals is strong, also when controlling for other competing tendencies. Given our ethnographic understanding of this research site, e.g., that the families that have lived and worked in this area for generations tend to form a close-knit community (Johnson, 2016), this finding is not surprising. Thus, partial support is found for H3a.

However, Models 4a/b show another interesting trend when considering how certain stakeholders form ties across the project's duration (and not necessarily with those of the same stakeholder category). These models capture the lower-order tendencies for homophily by including the *covariate same effect (egoX)* for individual stakeholder categories. Looking closely at these findings reveals a shift in tendencies for two particular stakeholder categories (researchers and locals) across the time period of the study. Both researchers and locals experienced an increased tendency to develop mutual understanding ties by the end of the ICRA project. Researchers began, in period 1, with a lower tendency to have mutual understanding ties relative to other roles (indicated by the negative, significant coefficient for the *egoX effect* in Model 4a), and this tendency switched by period 2, i.e., researchers exhibited a relatively strong tendency for forming mutual understanding ties with others (as shown by the positive, significant coefficient for the *egoX effect* in Model 4b). A somewhat similar pattern is evident with locals: in the first period, Local stakeholders did not exhibit any particular tendency for forming mutual understanding ties in the first period, yet by the second period (Model 4b), this tendency became relatively strong and positive, (as shown, again, by the positive, significant coefficient for the *egoX effect* in Model 4b).

Taken together, the tendencies found in Models 3a/b and 4a/b indicate that *local stakeholders, in particular, maintained a strong preference for nominating one another (*i.e. *other locals) as understanding, yet by the project end, these locals increased their tendency to form mutual*

Table 4
Descriptive statistics of climate change perception scores.

	Wave 1				Wave 2			Wave 3		
	Mean	SD	Missing		Mean	SD	Missing	Mean	SD	Missing
CC perception	4.415	(1.02)	19		4.192	(1.29)	8	4.167	(1.34)	18
Period 1 difference scores (counts)										
		Score	-2	-1	0	1	Missing			
		Count	2	3	30	4	21			
Period 2 difference scores (counts)										
		Score	-1	0	1	3	Missing			
		Count	3	29	1	1	26			

Table 5
SIENA models for period 1 (wave 1 and 2).

		Model 1a (H1)			Model 2a (H2)			Model 3a (H3a/b)			Model 4a (full)		
H#		par.		(s.e.)	par.		(s.e.)	par.		(s.e.)	par.		(s.e.)
	Network selection model												
	Mutual understanding (waves 1–2)												
	rate	7.595		(1.640)	7.455		(1.225)	7.615		(1.598)	7.397		(1.308)
	degree (density)	-2.605	* **	(0.255)	-2.566	* **	(0.231)	-3.212	* **	(0.330)	-3.182	* **	(0.434)
	gwesp 0.69 (transitivity)	1.380	* **	(0.170)	1.350	* **	(0.160)	1.396	* **	(0.181)	1.445	* **	(0.202)
H1	from Co-attend to Mutual understand	0.186	* *	(0.060)	0.188	* *	(0.060)	0.227	* **	(0.064)	0.195	* *	(0.063)
	Stakeholder type												
	Local ego										0.217		(0.494)
	Res ego										-0.585	†	(0.310)
H3a	same Local							0.440	*	(0.213)	0.713	* *	(0.266)
	same Gov							0.215		(0.188)	0.330		(0.212)
	same Res							0.202		(0.191)	-0.059		(0.211)
	CC perceptions (waves 1–2)												
	CC perceptions ego										-0.181		(0.253)
H3b	CC perceptions similarity							0.232		(0.380)	0.571		(0.727)
	Attribute model (CC perceptions)												
	Attribute: CC perceptions (waves 1–2)												
	rate				1.019		(0.409)				1.032		(0.447)
	Linear shape				1.154	*	(0.548)				1.173	†	(0.620)
	Quadratic shape				0.671		(0.503)				0.704		(0.479)
H2	CC perceptions similarity				-0.028		(0.650)				-0.031		(0.712)
	Overall maximum convergence ratio	0.041			0.106			0. 107			0.182		

Note: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; overall maximum convergence is an indicator of the extent to which simulated values of the statistics deviate from their target, observed values. When this ratio is 0.25 or lower, this is an indicator of good model convergence.

Table 6
SIENA models for period 2 (wave 2 and 3).

		Model 1b (H1)			Model 2b (H2)			Model 3b (H3a/b)			Model 4b (full)		
H#		par.		(s.e.)	par.		(s.e.)	par.		(s.e.)	par.		(s.e.)
	Network selection model												
	Mutual understanding (waves 2–3)												
	rate	5.254		(0.686)	9.133		(1.421)	5.496		(0.738)	8.807		(1.490)
	degree (density)	-3.521	* **	(0.448)	-3.199	* **	(0.450)	-4.098	* **	(0.611)	-4.219	* **	(0.490)
	gwesp 0.69 (transitivity)	1.876	* **	(0.285)	1.662	* **	(0.278)	1.871	* **	(0.318)	1.601	* **	(0.219)
H1	from Co-attend to Mutual understand	0.834	* **	(0.172)	0.615	* **	(0.138)	0.838	* **	(0.197)	0.582	* **	(0.134)
	Stakeholder type												
	Local ego										1.356	*	(0.566)
	Res ego										0.619	†	(0.383)
H3a	same Local							0.528	*	(0.241)	0.617	* *	(0.224)
	same Gov							0.531	*	(0.232)	0.207		(0.227)
	same Res							-0.212		(0.247)	-0.165		(0.200)
	CC perceptions (waves 2–3)												
	CC perceptions ego										0.177		(0.183)
H3b	CC perceptions similarity							-0.026		(0.409)	0.648		(0.469)
	Attribute model (CC perceptions)												
	Attribute: CC perceptions (waves 2–3)												
	rate				0.765		(0.352)				0.762		(0.356)
	Linear shape				1.931	†	(1.087)				2.033	†	(1.056)
	Quadratic shape				0.142		(0.381)				0.258		(0.362)
H2	CC perceptions similarity				-0.741		(0.875)				-0.695		(0.748)
	Overall maximum convergence ratio	0.054			0.140			0.089			0.090		

Note: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; overall maximum convergence is an indicator of the extent to which simulated values of the statistics deviate from their target, observed values. When this ratio is 0.25 or lower, this is an indicator of good model convergence.

understanding ties across the network, moving beyond their own stakeholder category.

With regards to model-fit, we refer readers to the goodness of fit (GOF) tests, found in Supplementary Material 1, which demonstrate that we have adequately captured network patterns in our empirical networks via our model specifications.

5. Summary and discussion

We developed a conceptual framework pertaining to participation (co-attendance), mutual understanding, and social learning (Fig. 1), and we used a longitudinal network approach to test this model. In developing this framework, we called attention to mutual understanding as a type of social relation that is discussed in the literature, yet not empirically tested as we demonstrate here. We found support for the idea that co-attendance leads to mutual understanding among stakeholders, and moreover, this tendency increased over time between locals and other stakeholders. In the context of ICRA, increasing mutual understanding between locals and non-locals was especially important, as past DIP research had shown that locals tended to shy away from both government and scientists (Johnson, 2016), and rather rely on the close-knit community found on the island.

In contrast, we found no support for actors becoming more similar in their CC perceptions to their networked partners. This calls for some reflection. The evidence for knowledge outcomes such as shared understandings that result from participatory processes varies greatly in the literature (see recent review by Karcher et al., 2021), and some argue that changing participants' attitudes towards one another (e.g., mutual understanding) is not only more likely, but possibly even *more important* than changing core beliefs or perceptions about environmental problems (Johnson et al., 2018; Miller Hesed et al., 2020; Walker and Daniels, 2019). In the context of the ICRA, stakeholders engaged with the overall project, discussed with one another the common issues impacting the DIP, and by the end of the project, the network as a whole achieved the collective outcome of generating a research report on climate change impacts to the DIP (Johnson et al., 2018; Paolisso et al., 2019). Such gains were accomplished in absence of evidence demonstrating any major shifts in CC views (we again refer readers to Table 4, which shows very few stakeholders shifting their views over the course of this project). As such, this lack of a shift in perceptions was, arguably, unnecessary for meeting certain aims of the ICRA project.

In addition, past research on social learning outcomes suggests that *the duration of a project* can impede social learning goals (Measham, 2013; Reed et al., 2010). In projects composed of heterogeneous stakeholders, a substantial amount of time may be needed for sharing, and the rise of mutual understanding and learning, and project-resources are often depleted before such processes fully unfold. Thus projects sometimes end before 'deeper' forms of learning can happen (Measham, 2013; Garmendia and Stagl, 2010). Some ICRA participants expressed, anecdotally, disappointment over the project ending, and some project members, sought and secured additional funding as a means to extend and solidify the goals and processes begun in the ICRA.[1] Thus, with more time, and hence more opportunities for attending participatory events together, more similarity in views among stakeholders may have emerged, and this is a potential area for future research.[2]

There are other future research directions implied by the current study. First, teasing apart mutual understanding from changes in perceptions indicates the need for more studies of this sort, ideally across longer periods of time and with larger samples, to both challenge and replicate this study's findings, and to also refine certain aspects of the research design. Second, additional measures for understanding, beyond the ones used here, may provide subtly different dimensions beyond those captured in a single measure. For example, perhaps attitudinal measures on understanding, such as whether stakeholders, in general, felt understood by others may have revealed a difference between understanding measured on the dyadic level, versus understanding in a more general sense. In addition, perhaps stakeholders may have felt more understood on certain topics versus others, and measures designed to capture those differences in topical understanding would reveal other patterns. Future research may also consider other kinds of social relations that might influence changes in CC perceptions or mutual understanding, such as frequency of communication, collaboration, or belonging to the same organization. For example, our measure for 'local stakeholders' potentially captures (albeit indirectly) everyday encounters such as locals bumping into each other, but gathering data explicitly on such relational encounters may expand on the role played by relations existing outside of the participatory process. Finally, survey-based studies with large samples suggest that demographic variables such as gender, age, and socioeconomic class are important drivers of climate change perceptions and risk (Xie et al., 2019). As such, future studies with larger-sized networks might be able to incorporate some of these variables of interest as well.

Taken together, our study offers firm support for the idea that participation can lead to the social outcome of mutual understanding, even among stakeholder categories that traditionally feel more marginalized to environmental governance discussions (Karcher et al., 2021). As such, this paper furthers the discussion on *which kinds of relations one can expect participatory processes to engender and support*. Said differently, scholars and decision makers are beyond the point of simply noting that social networks matter in the context of environmental governance, and instead, it is time to begin specifying and testing which networks ought to make a difference, and under which conditions. Towards this end, we encourage future network scholars to also adopt longitudinal approaches for studying these kinds of participatory projects as they unfold over time, thus bringing greater clarity to the sequential nature of key concepts, specific relations, and expected outcomes. As stakeholder engagement continues to grow as a strategy for improving environmental governance challenges on a number of fronts (Chambers et al., 2021; Horlings et al., 2021), developing coherent, conceptual models that can be tested from a network approach will increasingly be needed to help establish the link between good scholarship and practice.

Declaration of Competing Interest

The authors declare there is no conflict of interest. The funders had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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[1] Please visit the project's website for more details: https://www.dealislandpeninsulapartners.org/faith-communities-coastal-resilienc

[2] However, we wish to also note some limitations of this study, and how these may have impacted our results. The small size of our network (n = 60), coupled with the fact that these data were modeled as two separate time periods, may have been a contributing factor to not finding a significant result in our models; simulation studies using a SAOM approach have shown that it is difficult to acquire statistically significant coefficients for perception/behavior effects when networks are small in size (Stadtfeld, 2018).

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2022.02.006.

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