Assessing information-sharing networks within small-scale fisheries and the implications for conservation interventions

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Abstract

The effectiveness of biodiversity conservation interventions is often dependent on local resource users' underlying social interactions. However, it remains unclear how fine-scale differences in information shared between resource users can influence network structure and the success of behaviour-change interventions. We investigate this knowledge gap by comparing information-sharing networks in a fishing community in Peru where a trial conservation intervention is underway to reduce the incidental capture of sea turtles (*bycatch*). We show that the general network structure detailing information sharing about sea turtle bycatch differs from other fishing-related information sharing, specifically in degree assortativity (homophily) and eccentricity. This finding highlights that fine-scale differences in the information shared between resource users may influence network structure.

Introduction

The conservation and management of common-pool natural resources such as fisheries often involve behaviour-change interventions with resource users [1, 2]. These include interventions like the enforcement of rules, social marketing, and education campaigns [3-5]. Informed by other behavioural-change disciplines like public health and social marketing, the fields of conservation science and natural resource management are increasingly looking to understand the social structure of communities targeted for interventions, to predict how information flows influence the transmission of pro-environmental behaviours through social networks [6, 7].

Throughout the world's fisheries the incidental capture and mortality of marine organisms as bycatch remains a critical issue [8, 9]. Negative bycatch impacts are notably problematic for taxonomic groups with conservative life history characteristics like sea turtles, seabirds, marine mammals, sharks, and corals [10]. Moreover, managing bycatch is a particularly intractable issue among geographically dispersed populations of resource-constrained small-scale fishers in lower- and middle-income countries [11, 12].

Taking a social network approach to conservation issues like bycatch mitigation in small-scale fisheries can support our understanding of human behaviour by providing insight into particular social processes. For example, many conservation-orientated behaviour changes are complex, and adoption is through social influence [1, 13, 14] and social reinforcement [15], which occur through interpersonal communication, and the evaluation of credibility and social norms between peers [16-19]. In resource harvesting communities that lack institutional capacity and where state oversight is weak, such as small-scale fisheries, individual decision-makers are subject to fewer legal constraints and are more prone to influence by their peers [20]. For example, Alexander et al. [21] found that fishing experience dictates the influence among small-scale fishers in Jamaica, with older fishers and information brokers having discrete roles in shaping catch patterns for large- and small-sized fish species, respectively. In small-scale fisheries management, social network analysis has also proven useful for understanding the social dynamics of information sharing between fishers [22], considering the establishment of common rules and norms among stakeholders [23, 24], and understanding complex social-ecological interactions to enhance conflict resolution strategies [25]. Now, it is becoming increasingly recognised that social networks offer a powerful lens through which to understand the social and ecological contexts in which conservation in enacted. As such, further research into understanding how network approaches developed in the social sciences relate to those developed in ecological science, and the benefits of all types of approaches for the many questions within social networks, will now be of great benefit.

We apply null models that incorporate pre-network data permutations to fisher information-sharing data, to explore a potentially crucial, but currently untested assumption when analysing social networks in conservation science and natural resource management – the structure of the network (i.e., which individuals are socially tied to one another, and who may share information) is consistent across different (albeit perhaps somewhat similar) information-sharing networks. This uncertain assumption implies that the social links measured in one network will also be important for spreading the conservation information of interest in another closely related network. For instance, in an exemplar and important study [26], it was intuitively assumed that information shared between fishers about fishing would be predictive of a finer-scale yet closely related environmental outcome – shark bycatch. Similarly, in a contemporary study [27] investigating how 'key players' were positioned implementing broad conservation objectives, the social networks were based on similar information-sharing data mapping whom respondents fished with or exchange information about fishing. However, the most influential individuals in one economic or social network may not be the most influential people in a closely related information-sharing network, potentially changing expectations of individuals' influence regarding a specific conservation intervention.

If individuals' social behaviour remains consistent across different aspects of their social lives, in terms of which individuals they form links with and the number of links they form, then the social networks across these contexts are expected to be correlated [28, 29]. As individuals who share information to a particular topic, they may be more likely than a non-connected pair of individuals (dyad) to share a different topic of information (i.e., two gillnet skippers who know each other versus two that do not know each other). We, therefore, hypothesised that information-sharing networks across the assessed information types that relate to fishing would be correlated. However, specific networks may be strongly correlated to one another, while other networks may be less correlated.

We focus on a coastal fishing community in Peru with problematic sea turtle bycatch [30-32]. At the study site, a local not-for-profit is undertaking a trial community co-management bycatch reduction scheme [33]. This initiative intends to create direct incentives for the sea turtle bycatch reduction by giving price premiums to fish caught by fishers that follow bycatch reduction guidelines such as using light-emitting diodes on nets [34]. Timely bycatch information is conveyed to fishers by the not-for-profit [35], which has a vision of expanding the community co-management scheme, first to more fishers within the target community, and second to similar communities along Peru's coast. This expansion could be more cost-efficient if the not-for-profit better understood how messages about the bycatch-reduction initiative's existence and aims might spread.

In this study, we assess whether networks of information-sharing about sea turtle bycatch are structurally similar to networks for other information related to fishing (Table 1). We test the assumption that knowledge about information-sharing social networks should be transferable to a related information-sharing network of interest (other fishing issues and sea turtle bycatch, in our case). We illustrate how null model analysis techniques used in the ecological sciences may offer more in-depth insights into the fine-scale structure of human networks than could be gained from simple centrality measurement methods, and we provide insight into comparing information-sharing networks within a social system of high conservation interest. We conclude by discussing our findings in the context of research priorities for conservation science and highlight how our result can contribute to predicting how new information and behaviours may spread socially.

Materials And Methods

Study system

San Jose, Lambayeque, Peru (6°46' S, 79°58' W) is home to 168 small-scale commercial gillnet skippers that fish throughout the year. We surveyed 165 fishers representing 98.2% of the gillnet skippers at the site between July–September 2017 (Fig. S2b, Table S1). Gillnet skippers in San Jose are known to capture sea turtles in high numbers [30, 31, 36]. Green turtles (*Chelonia mydas*) are captured most frequently, followed by olive ridley turtles (*Lepidochelys olivacea*), and leatherback turtles (*Dermochelys coriacea*) [33]. Five gillnet skippers and their crew are currently involved in a trial community co-management bycatch reduction scheme operating from San Jose that requires fishers to use light-emitting diodes on their nets to reduce sea turtle bycatch [34]. Skippers were deemed active if they fished from the San Jose port with gillnets in the winter of 1 July – 30 September 2017. The network was surveyed during winter as skippers actively fishing during these months are established fishers in the San Jose community throughout the year. We define gillnets as encompassing surface drift gillnets and fixed bottom gillnets in single or trammel net configurations. The total San Jose gillnet skipper population (n=168) was determined using a combination of membership lists of the two main fishing groups in San Jose, lists of boats towed in and out of the water with tractors, and key informant interviews (Supplementary Information).

Data collection

Detailed social network data was collected using a structured questionnaire with a fixed choice survey design. Respondents were asked to consider up to ten individuals with whom they exchange useful information about fishing and whom they considered valuable to their fishing success. We classified nine fine-scale information-sharing types about which we expect gillnet skippers to exchange fishing related information (Table 1). As each nominee was given by the respondents, they were asked to highlight which fishing-related information they discussed with each nominee. For each fishing-related information network, respondents were asked to consider relationships that they have had with other skippers, vessel owners, crew members, other fishery leaders, fishery management officials, members of the scientific community, boat launching/landing support, fish sellers/market operators, family members, and any other stakeholders they fished or shared information with about fishing. Respondents were not asked who they receive information from. Interviews were undertaken verbally and respondents were not shown the questionnaire where responses were written (Supplementary Information). Questionnaires were trialed with fishers (n=8) in the Santa Rosa fishing community 17 km down the coast from San Jose (Fig. 2a). Pilot study data were not included in this study's analysis. Fishers were interviewed in their native language (Spanish). Documented, free, prior, and informed consent was sought before respondents could take part in the study. This research has Research Ethics Approval (CUREC 1A; Ref No: R52516/RE001 and R52516/RE002).

Statistics and Reproducibility

Social network construction

A social network was created for each fishing-related information type (Table 1). In each network, the nodes were the individuals, and the binary directed edges were the nominations by one node (sender) of another node (receiver) for this information type. All analysis was carried out in R [37] using the igraph package [38] for visualising and processing the analysis and carrying out the network comparisons using the null models.

Structural differences across information-sharing networks

To investigate whether networks of information-sharing between individuals were similar across different information types, we examined the networks' structural properties in terms of their degree assortativity and the variance and mean of individual centrality (Table 2). To account for the effect of basic characteristics of the networks (e.g., number of links, degree distributions) we compared these observed summary statistics to null models, which allowed inference of structural differences and similarities over and above that expected from these simple differences using null models (Fig. 1). While the null model methods applied in the current study were developed in ecology, they are beginning to be used in human network analysis. For example, in the fields of epidemiology for assessing human contact tracing disease control measures [39]. In the supplementary information we explain additional analysis detail and include discussion of the reason for the null models applied.

Degree assortativity

The degree assortativity (or homophily) coefficient [40] measures the extent to which central nodes are connected to other central nodes, and peripheral nodes are connected to other peripheral nodes based on a particular trait. The level of degree assortativity [40, 41] in a network is known to have important social implications for the operation and emergence of competition and cooperation (e.g., fishers will work with others like them). Positive values demonstrate degree assortativity, with perfectly homophilous networks scoring 1, and negative values representing disassortment. When nodes of similar centrality are randomly distributed in a network (i.e., fully disassorted), those networks do not always score -1 due to the minimum value depending on the number of node types and the relative number of links within each group [40]. For each of the information-sharing networks, we first calculated the assortativity by in-degree (the number of nominations each interviewed skipper received). Degree assortativity measures the extent to which ‘individuals that are highly nominated are disproportionately connected to others that are highly nominated’ and ‘individuals that are rarely nominated are disproportionately connected to others that are rarely nominated’. This is the primary assortativity measure of interest as in-degree provides the measure of which individuals provide information to others. However, as individuals differed in the number of nominations they made within each information-sharing network, we also calculated the assortativity by out-degree (the number of nominations each interviewed skipper made) to examine whether individuals were also disproportionately connected to others who make a similar number of nominations as themselves. As social networks often show assortativity by degree, we predicted that all the information sharing networks would be positively homophilous by nominations made and nominations received (i.e., highly nominating and nominated individuals would be closely associated with highly nominating and nominated individuals, whilst peripheral individuals would be more likely to be connected).

Eccentricity

We aimed to consider node-level properties that depend on the structure of the social network (Table 2). For this purpose, we used node eccentricity (igraph package [38]) that measures how far a node is from the furthest other [42]. Although this metric describes a node’s position within the wider network, the range of potential values it can take is not overly affected by permutations of the network structure in comparison to other more vulnerable metrics (e.g., betweenness, clustering coefficient) which are innately dependent on multiple aspects of the set structure of the network and are intuitively expected to differ largely from permutations by default. Finally, this metric is also relatively fast to compute; this is particularly useful when calculating it for many iterations of null networks. As such, we computed the variation in eccentricity in ‘received nominations’ (in-eccentricity) for each of the information sharing networks.

Null models for structural differences

Drawing comparisons of network structure, correlations, and node positions across different networks requires particular consideration because the general structure of the network (such as the number of links or degree distributions) has a large effect on the observed values obtained from standard summary statistics. This structure can be taken into consideration by comparing networks to null permutations (controlled randomisations) of themselves and recalculating the same summary statistics on the null networks. Through comparing the observed values of the summary statistics to the distribution of those statistics generated from the null networks, insight can be gained into the actual differences between observed networks across other networks, over and above what is expected from simple properties such as the number of links.

When calculating summary statistics (in-/out-degree assortativity, eccentricity) of each of the information-sharing networks, we also compared these to the values generated from permuting each of the networks separately. Specifically, we carried out edge permutations. The first edge permutation simply allowed the randomisation of all in-going links, while maintaining the number of nominations (out-going links) each individual made within this information-sharing network (termed edge null model 1 - Fig. 1a). The second edge permutation was a more conservative version of this, allowing swaps of links (which individuals nominated which other individuals in this information-sharing network) but maintaining the number of nominations each individual made in this information-sharing network (termed edge null model 2- Fig. 1b). Separately, for each of the information-sharing networks, 1000 permuted networks (of both of these permutation types) were generated and the distribution of the summary statistics were calculated for them.

Cross-network correlations

To reveal the extent to which the sea turtle bycatch information-sharing networks can be predicted from the other networks evaluated, we examined the dyadic similarity between the different information-sharing networks. We used cross-network null models to compare the expected correlation between each network and subsequently determined how the observed correlation between each network was driven by fine-scale structure over-and-above that expected from the system's general social structure. To examine the relationship between each network of dyadic information-sharing nominations, we calculated the correlation between the dyadic nominations on the unfolded network matrices. This approach is somewhat analogous to the Mantel test [43] (that tests the correlation between two matrices), yet as the networks were directed (and non-symmetrical), this was applied to the entire matrix rather than the lower triangle part (but excluding the diagonals because ‘self-nominations’ were not possible). The calculated correlation statistic represented the similarity/dissimilarity in the directed dyadic nominations amongst networks (who nominates whom), and these were compared to the distribution of the correlation statistic generated from the null models. To infer the extent to which networks are more, or less, similar than expected under the general dyadic social structure, we carried out a cross-network null model: For each dyadic nomination across any of the networks, we randomised the networks that these nominations were made within (termed ‘cross-network null model 1’ – Fig. 1c). As an even more conservative version of a cross-network null model, we created a new version of these permutations and controlled for the number of nominations that took place overall within each network (termed cross-network null model 2 – Fig. 1d; Fig. S7, S8).

Results

We constructed nine full fishing-related information-sharing networks (Methods). Of the 165 skippers surveyed, 151 nominated at least one gillnet skipper from the site as a key contact they talk to about fishing success, while 116 fishers from the site were nominated at least once by other fishers surveyed. The networks resulted in a total of 427 fisher-to-fisher nominations (i.e., links between the 165 skippers interviewed) for one network or more (Table S1). On average, fishers had 2.8 fisher-to-fisher contacts with whom they had formed communication links specific to fishing. Information-sharing networks per nomination averaged 7.7 (range 1-9). Fishers received on average 3.7 links (range 1–15) for one or more information-sharing network. Across the nine information-sharing networks evaluated (Table 1), sea turtle bycatch was discussed by fishers the least (61.6% of possible fisher-fisher links). In contrast, fishing location and fishing activity were discussed by fishers most frequently (both in 97.9% of the possible fisher-to-fisher links; Table S1).

Structural differences between information-sharing networks

We separately assessed degree assortativity (homophily) and node eccentricity of the sea turtle bycatch information-sharing networks and each of the other networks of information sharing related to fishing (Table 2). Across these networks, we compared how the observed statistics differed from edge-permutated versions of themselves. We considered the observed statistic to be significantly different from that expected under the null models when it fell outside the 95% range of the distribution of the statistics generated by the permutations (i.e., equivalent to significantly different at $p<0.05$ level in a two-tailed test).

Degree assortativity

For each fishing-related information-sharing network, we evaluated degree assortativity (the propensity for a fisher to be connected to others who are similarly (dis-)connected; referred to as degree homophily in the social sciences), as this is a primary structural component of the network [40, 41] (Table 2). We found that networks of sea turtle bycatch information-sharing nominations show no significant degree assortativity in comparison to the edge permutation null models (Observed stat: 0.038, edge null model 1: mean ± SD = -0.005 ± 0.059; $p = 0.512$, edge null model 2: mean ± SD = -0.011 ± 0.059; $p = 0.39$). As such, there was no evidence for a non-random tendency for highly nominated nodes to be disproportionately connected to other highly nominated nodes, nor for rarely nominated nodes to be disproportionately connected to other rarely nominated nodes. The sea turtle bycatch information-sharing network differed markedly in this regard from all of the other information-sharing networks' (Fig. 2c), all of which had significantly higher degree assortativity scores than expected from edge permutation null model 1. In addition, all the other information-sharing networks' had significantly higher degree assortativity scores than expected from edge permutation null model 2 apart from the 'weather' and 'technology' networks, which fell outside the top 5% of the null network degree assortativity coefficients but were not significantly different in the two-tailed test (edge permutation model 2 two-tailed $p=0.06$) (Fig. 2d).

Eccentricity

We found that sharing of information regarding sea turtle bycatch had a significantly lower variance in node eccentricity than expected under the null models controlling for simple properties such as the number of nominations and degree distributions (Observed stat: 14.71, edge null model 1: mean ± SD = 41 ± 13.5; $p<0.01$, edge null model 2: mean ± SD = 22.66 ± 5.335; $p<0.05$). Importantly, sea turtle bycatch information sharing was again unique in this sense (Fig. 2d), as none of the other information-sharing networks were significantly lower than expected under null permutations of themselves (Table S2). Six of the eight other networks showed significantly higher variance in node eccentricity than expected from a null model of their structure, which illustrates a particularly stark contrast from the sea turtle bycatch information-sharing network. These results demonstrate less variation in individuals' centralities across the gillnet skippers than expected in terms of sea turtle bycatch information sharing. In other words, gillnet skippers are more similar in how they share information about sea turtle bycatch with one another than expected, while this is not true for any other networks of information sharing. This conclusion also held when considering other measures of centrality. For supplementary information, we examined the variance in betweenness (as an alternative measure of centrality; Fig. S3) and mean eccentricity for each network's nodes (rather than the variance; Fig. S4). We also investigated the observed variance in node eccentricity in comparison to the null distributions (generated from the cross-network permutations; Fig. S5) and the observed mean node eccentricity in comparison to the null distributions (Fig. S6). The findings demonstrated that the sea turtle bycatch information-sharing network generally held some structural dissimilarities to all other fishing-related information-sharing networks.

Cross-network correlations of dyadic links

Gillnet skippers in our survey were asked to nominate individuals that they exchange useful information with about fishing and that they considered valuable to their fishing success. Respondents were then asked which type of fishing-related information they talk to each nominated individual about (Table 1). Given this system, we hypothesised that information-sharing networks across the assessed information types would be correlated with one another, assuming that pairs of skippers (dyads) who share information within a specific network would be more likely to share information in another network. As such, we expected all the other networks to significantly predict information-sharing within the network of particular interest (sea turtle bycatch information). Indeed, the sea turtle bycatch information-sharing network significantly correlated with all other networks (unfolded corr; $r = >0.7$; standard $p<0.01$). We also tested this observed correlation against that expected under the general social structure (cross-network null model 1 - who gains information from whom overall; Fig. 1c) as well as controlling for the probability of nomination within each network (cross-network null model 2; Fig. 1d). Under these null models, we found that the dyadic directed links within the sea turtle bycatch information-sharing network were significantly more correlated with four information sharing networks (regarding gear, locations, technology, and regulations – see Table 1) than expected under the general social structure (Fig. 3). Although the sea turtle bycatch information-sharing network held the highest raw correlation with networks of information regarding fishing locations (unfolded corr; $r = 0.78$), the largest difference between the correlation expected under the null models and the observed correlation was with information sharing regarding fishing regulations (unfolded corr; $r = 0.78$; mean expected corr cross-network null model 1 $r= 0.65$, mean expected corr cross-network null model 2 $r= 0.65$), suggesting that the fishing regulations network was particularly predictive of sea turtle bycatch information links given the underlying social structure of the system.

Discussion

By combining a fine-scale survey of a small-scale fishing community with a network null model approach that incorporates a pre-network data permutation procedure, we show that information-sharing networks about an issue of conservation concern (sea turtle bycatch) are structurally dissimilar from other closely related information-sharing networks that relate to fishing (Fig. 2), more so than expected by simple differences in an individual's degree (how many people they are connected to). We also demonstrate that specific fishing-related information-sharing networks can still be predictive of how information about sea turtle bycatch is shared between fishers, even more so than expected under the nomination structure of who nominated whom (Fig. 3).

Structural differences between information-sharing networks

We found that the sea turtle bycatch network did not show any degree assortativity (i.e. homophily - gillnet skippers talking to other gillnet skippers with a similar number of connections) despite the positive degree assortativity patterns across all other fishing-related information-sharing networks (Fig. 2c and Table S1). This finding indicates that the usual mechanisms that drive information sharing between gillnet skippers in the other fishing-related networks (and potentially social networks generally) are not at play in the sea turtle bycatch information-sharing network [40, 41]. The lack of discussion about sea turtle bycatch between gillnet skippers with similar levels of bycatch may potentially occur if some gillnet skippers with higher rates of sea turtle bycatch do not realise or appreciate that they have higher bycatch than other gillnet skippers in the community [44]. Indeed, previous research and field observations from the study site have suggested that fishers with higher bycatch rates tend not to put much effort into actively avoiding sea turtles captures unless they are specifically incentivised to do so (i.e., through the local not-for-profit's trial bycatch reduction initiative) [33]. Our degree assortativity results suggest that managers could incorporate an educational discussion with fishers on the local variations in sea turtle bycatch rates, prior to undertaking the planned expansion of the bycatch reduction strategy on trial, to improve how information about the sea turtle bycatch reduction intervention is shared between fishers.

We also found that the sea turtle bycatch information-sharing network has less variance in node centrality than expected, i.e., a more uniform individual-level network structure (Fig. 2d and Table 2). The low variance in node eccentricity indicates that the sea turtle bycatch network has a more homogenous network structure than the other networks (and many observed social networks, where high variability in node centrality is common and can result in high-degree nodes forming [45, 46]). This finding indicates that information about sea turtle bycatch will have less variation in the rate of diffusion throughout the San Jose skipper community, regardless of which skipper first started talking to other skippers in the community about the capture, compared to information-sharing in a network with higher variance in node eccentricity (e.g., the weather, fishing locations, fishing activity, and finance).

As an addition to the above points, we found less variance in node centrality (Fig. 2d) and less variance in mean eccentricity (Fig. S4) in the sea turtle bycatch information-sharing network when comparing to the cross-network null models (Fig. S5, S6). This lower variance shows that the variance and mean eccentricity is lower than expected, not just in comparison to the edge null models, but also lower than expected given the underlying social structure of who is connected to whom. This lower variance found when comparing the cross-network null models reinforces the hypothesis that the network's fine-scale structure (beyond who talks to whom) is contributing to these patterns. For example, certain personality traits that gillnet skippers hold, such as whether they would be willing to work with a local not-for-profit organisation to implement sea turtle bycatch reduction strategies on their boats in future, may be contributing to skipper centrality within the network. This finding demonstrates a particularly interesting use of comparing results across various null models that randomise different processes.

Cross-network correlations of dyadic links

Understanding correlations between networks allows for assessing skipper-to-skipper (dyadic link) information-sharing differences between multiple networks. Insight into these differences helps identify social contexts suited to conservation interventions, and more broadly, offers insight into the generalisability of network research [47].

We demonstrate that across all the networks assessed, the fine-scale structures of our information-sharing networks are more similar than otherwise expected based on the number of links or even who is linked to whom. While this similarity assures that in the current study’s gillnet skipper network, knowledge about a social network based on general information spread should be transferable into understanding how novel information spreads, the similarity also demonstrates that relying on simple network measures without the use of the null model comparisons could potentially result in an improper assessment of network structure. This result demonstrates the broad applicability of our network null model approach. We also show the networks that are most closely related to the specific network of conservation interest, offering a greater understanding of how information flows relevant to the broader topic of information-sharing about fishing are structured and relate to one another (Fig. 3).

Our results indicate that the fishing regulations network, followed by the vessel technology and maintenance, fishing gear, and fishing location networks, are more correlated with the sea turtle bycatch network structure than expected under the cross-network null models (Fig. 3). This finding gives insight into how fishers perceive information relating to sea turtle bycatch. For example, the correlation between sea turtle bycatch and the fishing regulation network could be because fishers perceive sea turtle bycatch as something they must abide by, similar to fishing regulations (related to the business and governance of fishing; Table 1). This correlation is supported by a supplementary structural analysis that shows that the sea turtle bycatch and regulation networks are structurally dissimilar concerning node variance to all other information sharing (Fig. S3, S9, S10). While these results begin to provide a more in-depth insight into how sea turtle bycatch information-sharing relates to other fishing-related information and how this information is perceived by fishers, further exploration is needed to determine the process underlying the structural differences identified.

Conclusion

We quantified the underlying structure of a small-scale fishery social system across nine information-sharing networks relating to fishing. Our study demonstrates how networks of information-sharing regarding a conservation-relevant topic (sea turtle bycatch) are structurally dissimilar from other fishing-related information-sharing networks, and the extent to which dyadic links can be non-randomly predicted from other information-sharing networks. Our results also show how null network approaches can be useful for identification of the extent of structural differences between networks and provides information about which other networks are best correlated with the conservation-relevant information sharing. Together these findings contribute understanding to how fine-scale differences in information shared between resource users can influence network structure.

Declarations

Data availability

The data and R scripts that support the findings of this study are available at https://github.com/JoshFirth/bycatch_information_flow.

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Competing financial interests. The authors declare no competing financial interests

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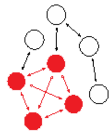
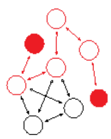
Tables

Table 1. Information-sharing networks that relate to fishing.

Full name	Short name	Description	Broad categorisation
Sea turtle bycatch	T.Bycatch	Sea turtle bycatch encounters including live releases and mortalities in nets.	Process of fishing, Business and governance of fishing
Gillnet type & maintenance	Gear	Changes made to net configuration (shifting rigging configurations from surface drift net to mid-water drift net or bottom-set net), and net maintenance.	Process of fishing
Weather conditions	Weather	Ocean and weather conditions (e.g., wind, swell).	
Fish location & catch sites	Location	Where fish might be located and where they have been travelling to fish.	
Fishing activity	Activity	How many people fishing, who is fishing, who caught what.	
Vessel technology & maintenance	Tech	Existing and new technologies used onboard the vessel (e.g., echo sounder, compass) and vessel maintenance (e.g., hull repairs, painting).	
Fishing regulations	Regs	Fishery policy and legislation.	Business and governance of fishing
Fishing finances	Finance	Market prices, loans, fines, penalties.	
Crew management	Crew	The hiring and instructing of crew onboard the vessel.	

Table 2. Network metrics used to assess information-sharing network structure. For network structure, red nodes (circles) and links (arrows) outline the represented metric in the network.

Metric	Network structure	Definition	Theoretical use in conservation-relevant systems	Example
Degree assortativity (homophily)		A preference for nodes to attach to others that are similar in some way (e.g., high-degree) [40]	Identifies individuals and pathways of individuals that could facilitate widespread diffusion of information about conservation initiatives in a community of conservation interest.	The authors use simulations of animal data to assess how variation in simple social association rules between individuals can determine their positions within emerging social networks. The results show that simple differences in group size cause positive assortativity and that metrics of individuals' indirect links can be more strongly related to underlying simple social differences than metrics of their dyadic links[48].
Node eccentricity		The furthest network distance between a node and all other nodes in the networks [42]. The equivalent to the inverse of some definitions of 'node closeness'	Can inform whether or not information relevant to a conservation initiative is shared in an even or clustered manner throughout a community on interest. This can inform how social norms and personal beliefs might affect information flow, which in turn can allow for conservation practitioners to tailor interventions to particular perspectives about a harmful activity (e.g., bycatch).	Using social network analysis and several centrality measures including 'node closeness' (also equivalent to the inverse of some definitions of 'node eccentricity') the authors assess the structural nature and expanse of climate-based communication between professionals across sectors in the Pacific Islands region. Their results show a simultaneously diffuse and strongly connected network, with no isolated spatial or sectoral groups. The most central network members were shown to be those with a strong networking component to their professions [49].

Figures

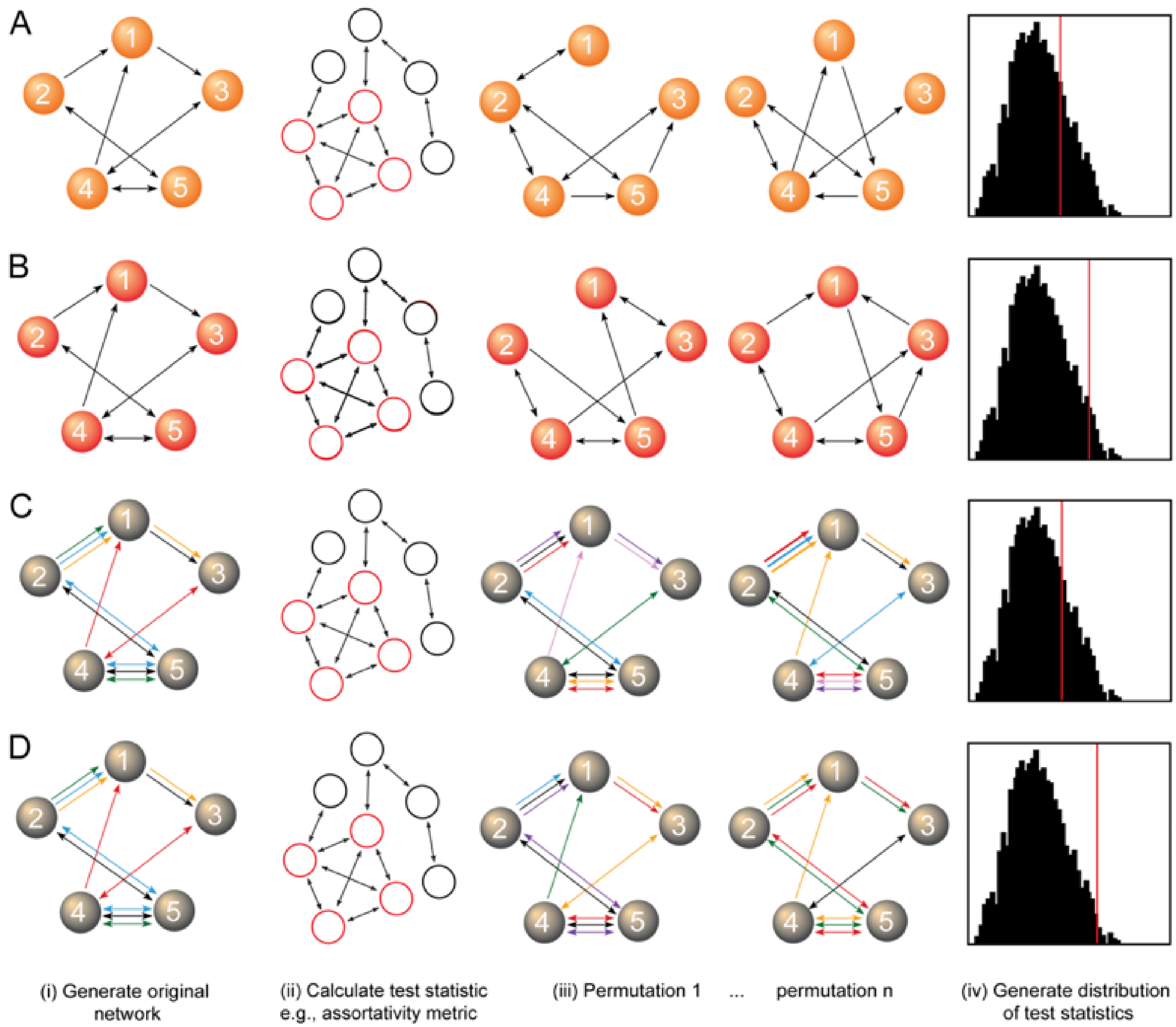


Figure 1

Schematic representation of edge-based permutation models with directed network data. Four main null model steps include (i) creating a social network from the observed data, (ii) calculating a test statistic, for example, a network-level metric like degree assortativity (high-degree nodes that are colored red primarily connect to other high-degree nodes), (iii) randomising the observation data (typically with 1000 permutations), and (iv) recording the distribution of possible test statistics. Conclusions can then by drawn by comparing the observed test statistics to the distribution test statistics, and the P-value calculated. Throughout the edge swap permutations, the node positions remain the same, but the configuration of edges between nodes change based on select criteria. The four null model examples shown are all used in this paper’s analysis. Edge permutation (A) allows the randomisation of all in-going links, whilst maintaining the number of nominations (out-going links) each individual made, (B) only allows the swap of links, by maintaining the number of nominees (in-going links) and nominations (out-going links) each individual made in this information-sharing network. The cross-network permutation (C) maintains each dyadic nomination, but randomises the networks that these nominations were made in (i.e., when individual X nominated individual Y for information sharing within three different information-sharing networks (represented by different colored arrows), the cross-network permutation allows these three nominations to be reassigned to any of the nine possible networks), and (D) maintains each dyadic nomination, but randomises the networks that these nominations were made in, while also controlling for the number of nominations that took place overall within each network (i.e., when individual X nominated individual Y for information sharing within three different information-sharing networks, these three nominations were reassigned amongst the networks in a way that was equal to the number of nominations in each network).

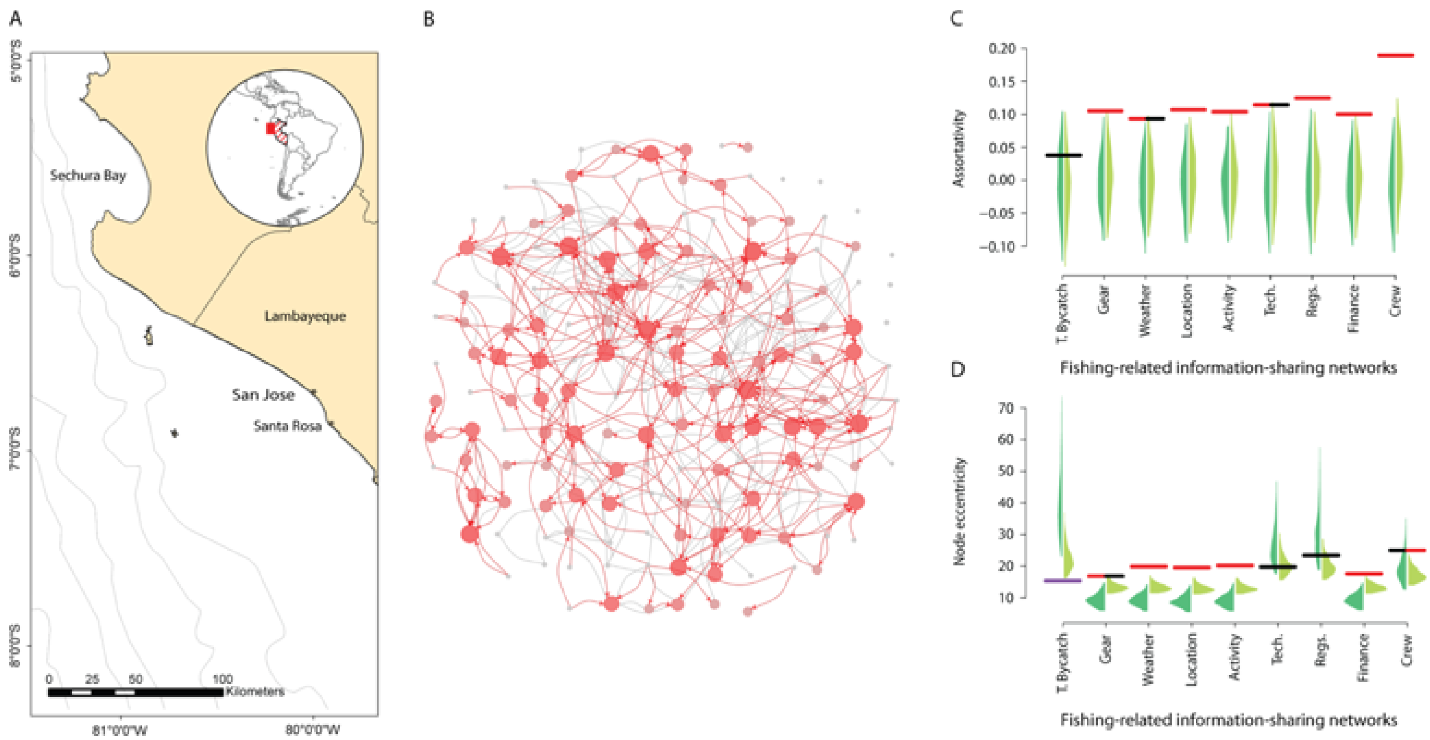


Figure 2

Structure of information-sharing in relation to sea turtle bycatch. (A) A map of the study site, San Jose, Lambayeque, Peru (6°46' S 79°58' W) and the surrounding coastline. Depth contours show 200, 1000, 3000, and 5000 meters (B) Illustrative network of the structure of information-sharing in relation to sea turtle bycatch. The nodes show each of the skippers and the adjoining lines show which dyads shared information in at least one information-sharing network, and nominations within the sea turtle bycatch network is highlighted as a directed red arrow here (arrow points to the one that was nominated). Node size and shading shows the number of nominations each individual received for sea turtle bycatch information (largest and most red = most nominations, small and grey = no nominations). Layout was set as a spring layout of edges across any network (to minimise overlap) and then expanded into a circular setting. See Fig. S1 for illustrative comparisons across networks. (C) The observed in-degree assortativity (homophily) in comparison to the null distributions for the different information-sharing networks, and (D) the observed variance in the node eccentricity in comparison to the null distributions for the different information-sharing networks. Horizontal lines show the observed values from the actual networks (red = observed values are above the permutations, black = observed values are within the range of the permutations, purple = observed values are below the permutations). Polygon distributions show those generated by permutations (dark green = outgoing edge permutation that maintains the no. of nominations each individual makes, light green = edge swap that maintains the no. of nominations each individual makes and also the number of times each individual was nominated). Due to differences in network factors, direct comparisons between the observed values are not informative. For details on each fishing-related information-sharing network assessed refer to Table 1.

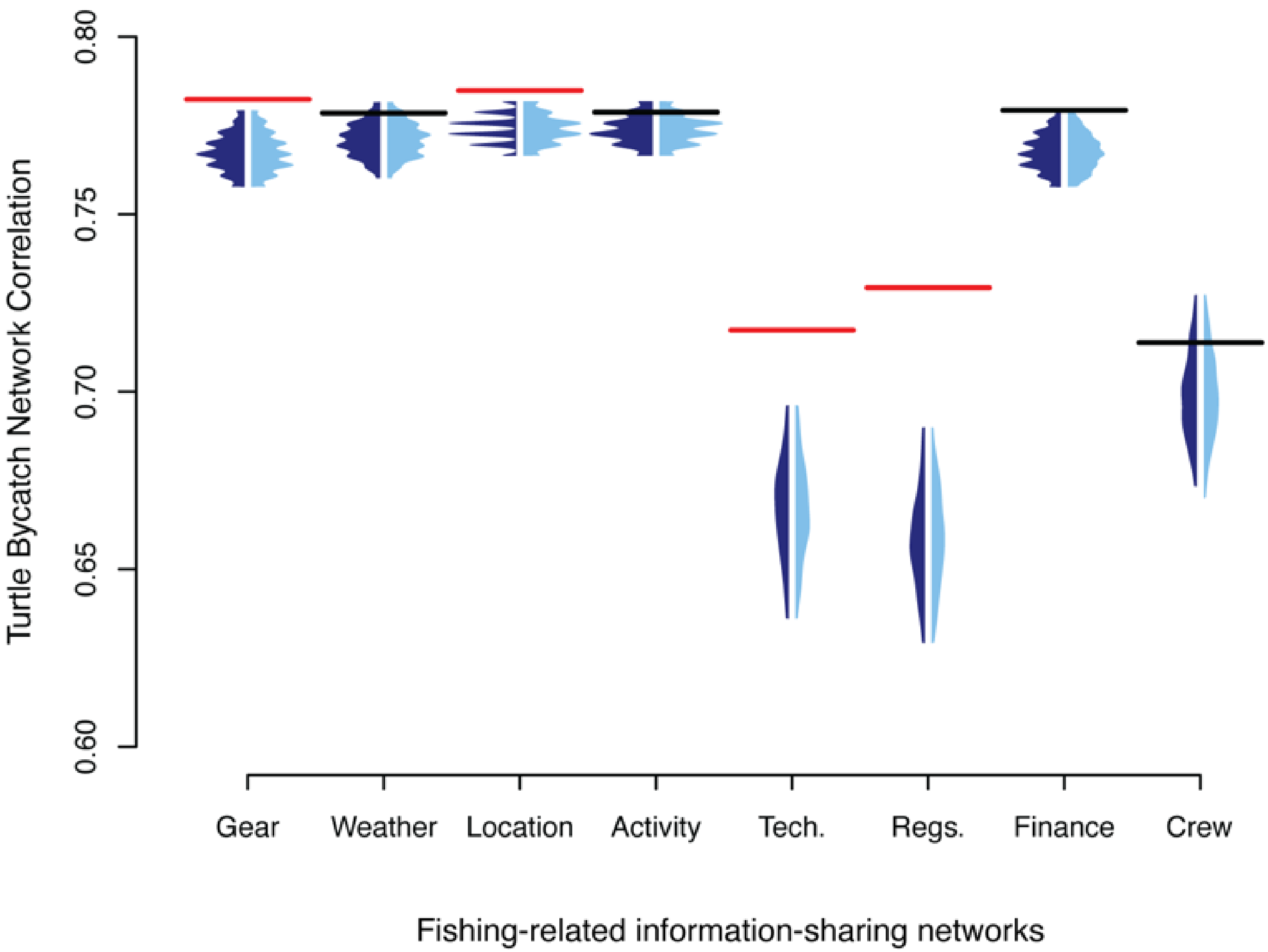


Figure 3

The observed correlation (and the correlations expected under the null models) between the sea turtle bycatch information-sharing network with all the other information networks. Horizontal lines show the observed values from the actual networks (red = observed values are above the permutations, black = observed values are within the range of the permutations, purple = observed values are below the permutations). Polygon distributions show those generated by permutations (dark blue = network swap that maintains the no. of nominations each individual makes and also the number of times each individual was nominated, but swaps the network these were made within whilst maintain the number of times each network was nominated as overall, light blue = conservative network swap that is the same as dark blue, but also maintains the number of networks each dyad nominated each other for – but changes those networks (same as a gbi permutation but on the dyad-by-network edges). Comparison between networks can be made by comparing the distance between the observed values from the actual networks (horizontal lines) and their associated permutation distribution (polygon) to the distance between the observed and associated permutation for each network. Due to differences in network factors, direct comparisons between the observed values are not informative. For details on each fishing-related information-sharing network assessed refer to Table 1.

Supplementary Files

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