Social networks and environmental outcomes

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Social networks can profoundly affect human behavior, which is the primary force driving environmental change. However, empirical evidence linking microlevel social interactions to large-scale environmental outcomes has remained scarce. Here, we leverage comprehensive data on information-sharing networks among large-scale commercial tuna fishers to examine how social networks relate to shark bycatch, a global environmental issue. We demonstrate that the tendency for fishers to primarily share information within their ethnic group creates segregated networks that are strongly correlated with shark bycatch. However, some fishers share information across ethnic lines, and examinations of their bycatch rates show that network contacts are more strongly related to fishing behaviors than ethnicity. Our findings indicate that social networks are tied to actions that can directly impact marine ecosystems, and that biases toward within-group ties may impede the diffusion of sustainable behaviors. Importantly, our analysis suggests that enhanced communication channels across segregated fisher groups could have prevented the incidental catch of over 46,000 sharks between 2008 and 2012 in a single commercial fishery.

social networks | environmental outcomes | homophily | shark bycatch | sustainability

As policy makers and natural resource managers struggle to devise effective strategies to sustain both natural and human capital in the face of growing human impacts, recent research has emphasized the importance of understanding relationships between social interactions and environmental outcomes (1–4). Social networks serve as primary channels for the flow of information and resources that facilitate human action (5, 6). Social interactions with our friends, family, and coworkers also directly affect our beliefs, decisions, and behaviors (7, 8). The degree to which information and behaviors spread through social networks is greatly affected by their structure (5, 9–11). One of the most basic factors governing social network structure is the principle of "homophily" (Fig. 1).

Homophily is a social selection process that describes the tendency for people to disproportionately form social ties with others most similar to themselves (12–14). It has been observed for various types of social relations, including friendships, marriage, and information sharing (12). Existing research on homophily shows that it can heavily influence the structure of social networks and their effects on people's lives (15–23). One of the most pervasive effects of homophily is that it can cause social networks to become highly clustered (13, 21, 24). Intuitively, clustered social networks consist of multiple groups of people who are more densely connected internally and more sparsely connected externally (Fig. 1). At the extreme, strong homophily-driven clustering can result in segregated networks, where social ties tend to be restricted within groups of similar people and largely fail to extend to groups that are different along some trait or set of traits (21). Segregation in social networks is important because it can inhibit communication and learning across groups (5, 9, 17), causing knowledge and behaviors to become localized in social space (12).

The effects of homophily-driven social network segregation in information-sharing networks is particularly important in the context of environmental systems. Environmental systems are often characterized by diverse groups of actors competing over limited resources where individual decisions and behaviors can have substantial impacts on ecosystem health (25). Because environmental systems are inherently dynamic and complex, information that can support decision making in this context can be a highly valuable resource and is not shared indiscriminately (26). Indeed, in line with the literature on homophily, existing research suggests that actors in these settings often choose to primarily share information with others most similar to themselves, creating somewhat distinct social groups (24, 27). Due to heightened competition for limited resources, any behavioral differences across groups that potentially emerge from this preference for within-group ties can be further exacerbated (28, 29). Thus, in environmental systems characterized by diverse groups of actors and high levels of competition, homophily-driven social network segregation is likely to hinder the diffusion of information and associated behaviors across dissimilar groups (12). This is of particular concern when the information or behavior leads to more (or less) sustainable environmental outcomes.

To understand the link between social networks, homophily, and environmental outcomes, we interviewed nearly every fisher in Hawaii's tuna longline fishery about who they regularly exchange valuable information with about fishing (*Supporting Information*). These data allowed us to create a network of information exchange within the fishery, which we refer to as the "information-sharing network." We also leveraged data on shark bycatch rates as an example of an environmental outcome. Using this information, we tested the hypothesis that homophily-driven social network segregation can result in divergent behaviors that have

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Significance

Understanding how social dynamics drive outcomes in environmental systems is critical to advancing global sustainability. We link comprehensive data on fishers' information-sharing networks and observed fishing behaviors to demonstrate that social networks are tied to actions that can directly impact ecological health. Specifically, we find evidence that the propensity for individuals to share information primarily with others most similar to themselves creates segregated networks that impede the diffusion of sustainable behaviors—behaviors that could have mitigated the incidental catch of over 46,000 sharks in a single commercial fishery between 2008 and 2012. Our results suggest having a better understanding of social structures and bolstering effective communication across segregated networks has the potential to contribute toward more sustainable environmental outcomes.

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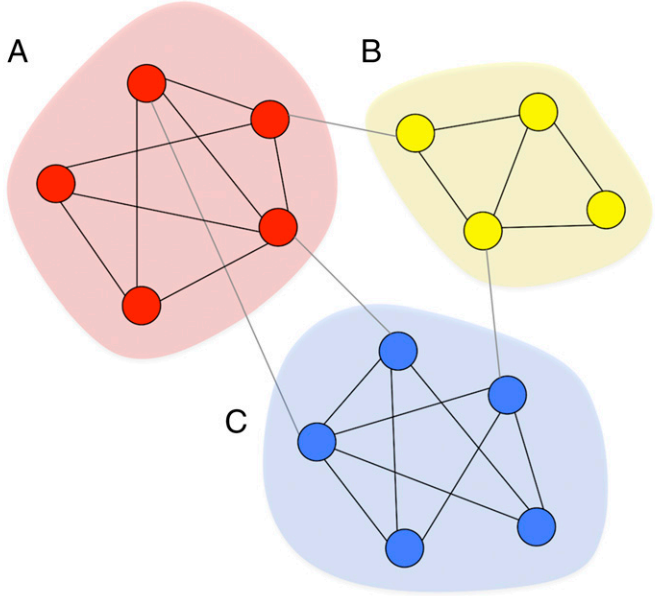

Fig. 1. Homophily, social network structure, and causal mechanisms. A depiction of three network communities (*A*–*C*) where nodes represent people and colors represent individual traits. People in the same community are more likely to be similar (same color node) and to adopt the same ideas and behaviors. This is the principle of homophily. There are two potential causal mechanisms at play here: (*i*) Social selection: similar people are attracted to each other and tend to form social ties (e.g., blue nodes tend to form ties with blue nodes, red nodes tend to form ties with red nodes, etc.). This can lead to the formation of dense communities segregated by ethnicity, race, gender, or other traits, such as those depicted here. (*ii*) Social influence/contagion: people are often influenced by those in their social network through the diffusion of information and the pressure to conform. This is sometimes referred to as peer effects and it is thought to be stronger among people who are already similar in other ways. For example, someone in community C is more likely to be influenced by others in community C than by those in community A, even if they have exposure to community A. Inevitably, this can cause similar people to become even more similar over time. A critical challenge in most empirical work attempting to make casual network claims is thus disentangling social influence from social selection processes (38): Are people similar because they are socially connected (and therefore subject to social influence), or are similar people simply forming ties with each other in the first place (social selection)?

important implications for ecosystem health. Although shark bycatch rates exhibit a high level of variability related to spatiotemporal factors such as prey abundance and sea surface temperature, they can also be influenced by fishing behaviors (30). Thus, our hypothesis rests on the assumption that fishing behaviors are in some part influenced by information access and the larger structure of fishers' information-sharing networks. Specifically, because catching sharks can be both dangerous and costly for longline tuna fishers in Hawaii (31), we assume there is an incentive to avoid shark bycatch, and that a fisher's information-sharing network provides a means by which they can obtain information to aid them in selecting and implementing bycatch avoidance behaviors. These behaviors may include changing bait, sharing information about how to accurately identify high shark areas, observing lunar and seasonal patterns, or cooperating to actively avoid bycatch hotspots while at sea. In line with the literature on homophily and social network segregation (5, 12, 32), we expect that actual adoption of particular strategies are more likely to occur within more densely connected communities driven by preferences for within-group ties (homophily) and may not cross over to other groups (17, 33), resulting in divergent fishing behaviors that can directly impact shark bycatch and indirectly impact ecosystem health.

We observe strong homophily based on ethnicity within the information-sharing network, i.e., the network is highly segregated along ethnic lines, creating distinct information-sharing network groups that largely correspond to ethnicity (Fig. 2). As we show in the following section, ethnic groups also demonstrate divergent behavior in terms of our environmental outcome: rates of shark bycatch differ across groups. This is suggestive evidence that segregated information-sharing network groups driven by ethnic homophily are influencing bycatch avoidance behavior, and that these behaviors are not diffusing from one group to another. This finding is very much in line with the literature on the effects of homophily and social network segregation (5, 12, 17, 32). However, as highlighted in Fig. 1, a challenge exists in conclusively attributing differences in shark bycatch to the influence of information-sharing networks. First, in addition to choosing information-sharing partners from the same ethnic background (social selection), fishers could be choosing information-sharing partners with similar bycatch avoidance behaviors (an additional form of social selection). Although this is unlikely given that bycatch is a by-product of a competitive economic pursuit (tuna fishing), we nonetheless discuss this possibility in the following section. Second, and more critically, it is possible that culturally embedded norms correlated with ethnicity may instead be influencing fishing behaviors, but the near-perfect association between ethnicity and information-sharing groups makes it difficult to disentangle these two potentially competing explanations. Interestingly, a number of "outliers" exist in the network. These actors do not form networks according to ethnic homophily: they mostly share information with ethnic groups that are different to their own. In the next section, we present empirical evidence that these actors behave in accordance with their network contacts (that is, the average behavior of the information-sharing group they have a majority of ties to). Thus, our results indicate that network contacts are more strongly related to behavior than ethnicity, suggesting that social networks are indeed tied to environmental outcomes.

Our environmental outcome of interest—fisheries bycatch—is a significant global issue. From an ecological perspective, high rates of bycatch can cause population declines, remove top predators, and alter the foraging behavior of proximate species (34). From an economic perspective, bycatch is often discarded, which is extremely wasteful (31). When a bycatch species is a target species for a different fishery, this can cause conflict between different fishing fleets. Moreover, concern over bycatch is often the cause of increased regulation in fisheries, which can have adverse economic impacts on fishers and fishing communities (31). From a conservation perspective, many shark species have been classified as endangered, and bycatch represents a primary threat to shark populations worldwide (34). Importantly, our results suggest that complete diffusion of shark avoidance strategies across segregated information-sharing networks could have prevented the incidental catch of over 46,000 sharks between 2008 and 2012, providing support to our hypothesis that social network segregation can have important implications for ecosystem health.

Results and Discussion

Hawaii's longline fishery is a limited-entry, multimillion-dollar industry supplying domestic and international markets with fresh tuna and swordfish, and is the largest commercial fishing sector in the Hawaiian Islands. From 2008 to 2012, there were 122–129 active vessels that completed between 1,205 and 1,381 annual fishing trips generating revenues of $65 to $94 million USD per year (Fig. S1). The fishery is composed of three distinct ethnic groups: Vietnamese Americans (V-A), European Americans (E-A), and Korean Americans (K-A), all of which target tuna (primarily bigeye tuna, *Thunnus obesus*) for at least a portion of the year (24).

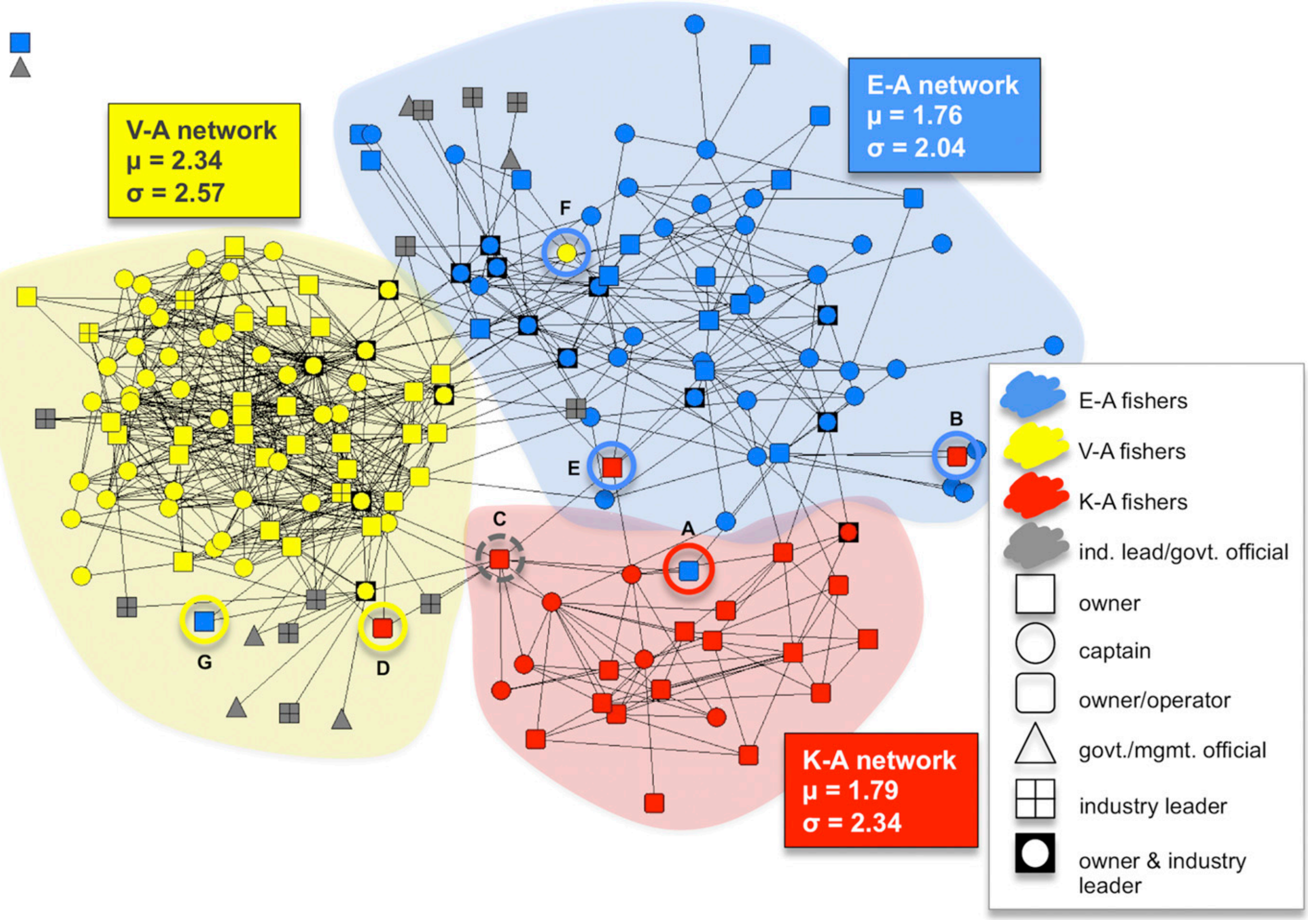

Fig. 2. Shark bycatch by information-sharing network group. Information-sharing networks in Hawaii's longline fishery generated in NetDraw (41) using the spring embedding algorithm. Each node corresponds to an individual fisher color coded by ethnicity, or an actor deemed important for information sharing by respondents (i.e., industry leader, government, or management official). Information-sharing groups are delimited by shaded backgrounds, the color of which corresponds to their dominant ethnicity. Two isolates not connected to anyone are located in the top left corner. Circled nodes denote outliers. Those with solid lines represent fishers who have a majority of ties outside their ethnic group, with the color of the circle corresponding to the group they have a majority of ties to. Those with gray dashed lines denote nodes with an equal proportion of ties both within and outside their ethnic group. Excluding these outliers, mean (μ) shark bycatch and SDs (σ) per 1,000 hooks in Hawaii's tuna longline fishery from 2008 to 2012 are reported by community. Although informative, these statistics do not account for the conditions under which fishers are operating, such as when and where they fish, which can substantially influence rates of bycatch.

We surveyed nearly all fishers in Hawaii's longline fishery about who they commonly exchanged important information with about fishing. This information-sharing network exhibits strong homophily (*Supporting Information*), with the majority of fishers organizing themselves into three distinct "network groups" corresponding to ethnicity (Fig. 2). Of the 159 fishers present in the network, only 6 have a majority of ties outside their ethnic group, whereas 1 has an equal proportion of intraethnic and interethnic group ties. We refer to these individuals as outliers. Excluding these outliers, we tested whether there was any observable difference in shark bycatch across these network groups using a sample of 12,062 observed tuna fishing sets from 2008 to 2012. The data on fishing sets, summarized in Table S1, were collected by federal fisheries observers onboard each vessel (*Supporting Information*).

An examination of the simple average number of sharks caught per 1,000 hooks across the 5-y period suggests a negligible difference between the K-A and E-A network groups, and a larger difference between the V-A and both other network groups (Fig. 2 and Table S2). However, the conditions under which fishers operate, i.e., when, where, and how they fish, is known to have a significant impact on shark bycatch rates (30, 35). When accounting for these factors (e.g., fishing location, vessel size, seasonality; see Table S3) in a negative binomial regression model, we find no evidence to suggest a difference between the K-A and V-A network groups (Table 1 and Table S4). However, our results show a statistically significant difference in shark bycatch between the E-A network group compared with both the V-A and K-A network groups (Table 1 and Table S4). In other words, segregation along ethnic lines in fishers' information-sharing networks appears to be correlated with differences in shark bycatch for some network groups.

Although our initial model result suggests homophily-driven social network segregation may influence environmental outcomes, clearly distinguishing this as a network effect rather than a preexisting cultural effect is somewhat problematic. Culture-related behavior can obviously diffuse through networks, but our concern here is culture-related differences that exist regardless of network links. Because the primary factor driving homophily in this fishery is ethnicity (24) (*Supporting Information*), this may be correlated with preexisting cultural differences that influence fishing behaviors independent of network interactions, e.g., cultural norms. However, the almost perfect association of homophilous information-sharing network groups with ethnicity rules out including ethnicity as a potential control in our original model. However, if ethnicity-dependent cultural norms are in fact driving

Table 1. The relationship between social network segregation and shark bycatch

	Regression	
Network group	1	2
E-A network	−0.217 (0.049)*	(Base)
K-A network	−0.031 (0.052)	0.187 (0.053)*
V-A network	(Base)	0.217 (0.049)*

Values shown are coefficients (and SEs) from two negative binomial regressions. The dependent variable is shark per fishing set in Hawaii's tuna longline fishery from 2008 to 2012 (n = 12,062). Controls accounting for the conditions under which fishers are operating include target species catch, vessel length, number of hooks, set location, soak time, temperature, type of bait, seasonality, lunar variability, and annual variability (see Table S3 for variable descriptions and Table S4 for full model results). SEs are clustered to account for multiple observations of 120 individual fishers.
*Significance at $P < 0.05$.

the differences in fishing behaviors we have observed here, we would expect those whose majority of ties fall outside their ethnic group (outliers) to be acting more like their ethnic group, rather than their network group, where their network group is defined as the group they have a majority of ties to.

To test for this effect, we examined whether observed outliers' rates of shark bycatch were significantly different from their ethnic or network group while accounting for the conditions under which they operate (i.e., when, where, and how they fish). Of the seven outliers, the observer data included observations for four (A–D, Fig. 2; Table S2). Although three of these outliers had a majority of ties outside their ethnic group (A, B, and D; Fig. 2), two (A and B) are of particular interest because they spanned network groups found to have significantly different rates of shark bycatch. Results from negative binomial regressions show that these two outliers had significantly different rates of shark bycatch than their ethnic group, but not significantly different from their network group, defined as the group they have a majority of ties to (Table 2 and Table S5). In short, they appear to be acting much more like their network group, rather than their ethnic group.

The two remaining outliers present in the observer data (C and D) spanned network groups with similar bycatch rates (the K-A and V-A network groups, Table 1). When accounting for the conditions under which they operate, their individual rates of shark bycatch are also in line with our hypothesis. Outlier D's rate was not significantly different from their ethnic or network group (K-A and V-A, respectively), yet was significantly different from the group they had no information-sharing ties to (the E-A network group; Table 2). The remaining outlier (C) had an equal proportion of intraethnic and interethnic relations, and their rate of shark bycatch was also not significantly different from their ethnic group (K-A) or the additional network group they had information-sharing ties to (V-A). Similar to D, it was, however, significantly different from the group they had no information-sharing ties to (the E-A network; Table 2). Although our analysis of outliers is inherently limited by the small number of them present in the network, these results lend empirical support for a network effect, rather than a cultural effect, being present in our original model, which included all fishers (Table 1). In other words, our results suggest that social affiliations are indeed tied to fishing behaviors that can have a direct impact on ecosystems.

We have presented evidence that social networks are related to environmental outcomes and that homophily-driven network segregation may impede the diffusion of sustainable behaviors. The magnitude of this impact is worthy of both scholarly and policy attention. A coarse analysis suggests that, if ties were less confined to ethnic groups and all fishers were able to access (and chose to act on) information that could aid them in achieving the same shark bycatch rate as the most efficient network group with the lowest rate (the E-A network group), interactions with ∼4,154 sharks directly observed in our sample might have been avoided. Applying this same rate to all hooks reported in federal logbooks on tuna-fishing trips, we estimate that, between 2008 and 2012, interactions with ∼46,339 sharks might have been avoided, representing an estimated 12% annual reduction in overall shark bycatch in Hawaii's longline tuna fishery alone.

As is the case with many scientific inquires, our results seem to uncover more questions than answers. Namely, what exactly is the more efficient group of fishers doing differently that has enabled them to mitigate shark bycatch more effectively than others? Information gathered post hoc from key informants suggest they may be cooperating at sea by sharing information about fishing locations to avoid shark bycatch hotspots. It was also suggested that they may have adopted updated technologies that facilitate more efficient fishing practices. Although available data allowed us to control for fishing location, we were unable to capture the dynamic behavior of fishers in time and space that would help quantify explicit cooperation at sea. Similarly, the fisheries observer data did not include detailed information on all of the updated technology each vessel was equipped with. Obtaining a clear answer to this question is, however, critical for informing effective policy and should be the focus of future research.

Common to other empirical inquires on network effects (36) and highlighted in Fig. 1, our approach suffers from some limitations. Namely, due to the cross-sectional nature of our network

Table 2. Are outliers acting more like their ethnic group, or their network group?

Regression	Coefficient (SE)
A. Regression with outlier A as the base, who is E-A with a majority of ties to the K-A network	
E-A network	**−0.171 (0.030)***
K-A network	**0.017 (0.055)**
V-A network	−0.047 (0.044)
B. Regression with outlier B as the base, who is K-A with a majority of ties to the E-A network	
E-A network	**−0.018 (0.066)**
K-A network	**0.169 (0.060)***
V-A network	0.200 (0.066)*
C. Regression with outlier C as the base, who is K-A and has ties split between the K-A network, the V-A network, and other nonfishers	
E-A network	−0.144 (0.067)*
K-A network	**0.045 (0.057)**
V-A network	**0.073 (0.042)**
D. Regression with outlier D as the base, who is K-A and has a majority of ties to the V-A network	
E-A network	−0.244 (0.051)*
K-A network	**−0.057 (0.044)**
V-A network	**−0.028 (0.040)**

Values shown are coefficients (and SEs) from four negative binomial regressions (A–D). The dependent variable is shark per fishing set in Hawaii's tuna longline fishery from 2008 to 2012 (n = 12,062). Network variables account for observed homophilous groupings along ethnic lines; outliers designate circled nodes in Fig. 2, which are independently tested to determine whether their rates of shark bycatch are significantly different from their ethnic or network group. Controls include target species catch, vessel length, number of hooks, set location, soak time, temperature, type of bait, seasonality, lunar variability, and annual variability (see Table S3 for variable descriptions and Table S5 for full model results). SEs are clustered to account for multiple observations of 120 individual fishers. In each model (A–D), the network groups in question are bold.
*Significance at <0.05.

data, the casual direction between social affiliations and environmental behaviors is difficult to statistically establish. It is clear in this case that ethnicity is a strong determinant of tie formation (social selection), and it is not possible for this trait to diffuse through networks the way information and behaviors can. However, the question of whether fishers also potentially organize themselves into information-sharing groups based on bycatch behaviors (an additional form of social selection), or whether bycatch behaviors are influenced by information-sharing groups (social influence) remains. Given the number of controls included in our model, the fact that bycatch is a by-product of the pursuit of an economic activity (tuna fishing), and the well-documented value of information in fisheries for supporting decision making and behavior (37), we believe the former is unlikely. However, firmly establishing the causal mechanisms underlying the observed correspondence between homophily-driven network segregation and behaviors affecting shark bycatch will require dynamic network data collected at multiple points in time (38), which does not currently exist. Such data could also enable future research to determine how individual fishers are influenced by the behavior of their direct contacts irrespective of network clustering or segregation effects, adding further insight into the relationship between social networks and environmental outcomes.

Despite the limitations of our data and empirical approach, our results offer evidence that patterns of social structure driven by homophily correlate with behaviors that can directly impact ecological sustainability. In other words, social networks appear to be tied to fishing behaviors that can scale up to have a direct impact on ecosystems. In this case, the conclusion is that one information-sharing network group of fishers exhibits more sustainable fishing behaviors that better mitigate shark bycatch, yet homophily-driven social network segregation appears to prevent these behaviors from being diffused and adopted by all fishers. Our results thus suggest having a better understanding of social interactions and bolstering effective communication across segregated networks has the potential to contribute toward more sustainable environmental outcomes.

Methods

Further details are provided in *Supporting Information*.

All fisheries catch and effort data were collected by the National Oceanic and Atmospheric Administration's (NOAA) Pacific Islands Regional Office Observer Program. Twenty percent of all Hawaii-based longline tuna trips are federally mandated to carry an onboard fisheries observer that collects detailed data on catch and effort for every fishing set. The observer data from 2008 to 2012 includes 18,059 fishing sets, of which 5,997 were missing key variables, resulting in a usable sample of 12,062 fishing sets from 867 observed trips made by 120 unique individual fishers. In the sample, a typical tuna trip lasted anywhere from 2.5–4 wk and was composed of ∼14 ± 4 fishing sets containing 2,327 ± 409 hooks each (Table S1). Across all sets in the sample, the mean rate of shark bycatch was 4.603 per fishing set (Table S1; Fig. S2).

The information-sharing network data are cross-sectional and were collected from primary decision makers in Hawaii's longline fleet from May 2011 to January 2012 (24). Primary decision makers are defined as vessel owners and captains, which we refer to collectively as "fishers." Fishers were specifically asked to identify up to 10 individuals with whom they regularly exchanged important information with about fishing. Fishers were also asked to report how often they shared useful information with each contact, how valuable they felt the information was to their fishing success, and the degree to which their fishery-related information-sharing contacts may have changed over the past 5 y. A high response rate was achieved, including 90% of all fishers tied to 93% of all active vessels during the time of data collection (*Supporting Information*). Research protocols were approved by the Institutional Review Board of the Office of Research Compliance Human Studies Program at the University of Hawaii at Manoa, and informed consent was obtained from all respondents.

Fishing can be characterized as a competitive economic pursuit—particularly in this fishery, which, unlike many other US commercial fisheries, has not been rationalized by the implementation of a rights-based management scheme (*Supporting Information*). In this context, information that may help fishers to better mitigate bycatch, such as information on bycatch levels in specific fishing locations, is not likely to be shared indiscriminately because it has the ability to increase the fishing efficiency of others (26, 39). To more accurately capture the specific information-sharing ties more likely to influence fishing behaviors that can affect shark bycatch, we did not use information-sharing ties identified by respondents as "not valuable" or that were used less frequently than one to three times per month. The resulting network included 179 nodes (159 of which are fishers), 857 ties, 138 reciprocal ties, a mean geodesic distance of 4.42, an average degree of 8.246 network neighbors, and three components: one weakly connected containing all but two nodes, and two isolates (Fig. 2). Degree distributions for the full network including all ties and the network we have described above are presented in Fig. S3.

To test our hypothesis, we used a negative binomial regression model due to the count nature of shark interactions (Fig. S4) and the prevalence of overdispersion. We accounted for the conditions under which fishers operate, i.e., spatiotemporal and operational factors known to affect shark bycatch, directly in the model. These variables included target species catch, vessel length, number of hooks, set location, soak time, temperature, type of bait, seasonality, lunar variability, and annual variability (see *Supporting Information* and Table S3 for explanations of each variable). We clustered SEs to account for multiple observations of the 120 unique individual fishers that were present in the fisheries observer data.

To estimate the number of sharks in our sample that might have been avoided under conditions of more complete information sharing across all network groups, we calculated the difference in shark catch observed in our sample compared with the number of sharks that would have been caught if all fishers had the same mean shark bycatch rate as the most efficient network group (the E-A network, 1.776 sharks per 1,000 hooks; Table S2). Scaling this up to account for all Hawaii-based tuna longline fishing trips taken between 2008 and 2012 (which includes both observed and unobserved fishing sets), we applied this same rate to all hooks reported in federal logbooks during this period. However, because federal logbooks are known to contain systematic underestimates of shark bycatch (40), rather than comparing it to the total number of sharks recorded in logbooks over our study period, we compared it to an estimated total number of sharks caught in both observed and unobserved trips, using the mean shark bycatch rate for all fishers observed in our sample (1.996 sharks per 1,000 hooks; Table S2).

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