Canadian Science Publishing

ARTICLE

Association networks in the Dutch offshore beam trawl fleet: their predictors and relationship to vessel performance

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Abstract: Networks play a key role in the functioning of socioecological fishery systems. Most network studies among fish harvesters examining fishing success utilize interviews and questionnaires. Though insightful, such studies are resource and time-intensive and thus unlikely to be replicated frequently through time. Alternatively, commercial landings records and vessel monitoring systems (VMS) provide continuous sources of information that can be used to examine variation in vessel networks through time. We used VMS data to define association networks among vessels. Relationships were found between common network metrics and annual performance based on landings data. Associations between vessels were more closely examined as a function of annual activity, performance, favoured species, and landing port using temporal exponential random graph models. We examined network dynamics across 4 consecutive years. Changes in vessel associations were clearly related to performance, landing port, and species targeted. Network structure could affect the relationship between catch and nominal effort, influencing stock assessments and responses to management actions. Our methodology provides a means to follow network change, identifying situations where more detailed study is warranted.

Résumé : Les réseaux jouent un rôle clé dans le fonctionnement des systèmes socioéconomiques de pêche. La plupart des études sur les réseaux de pêcheurs qui examinent le succès de la pêche ont recours à des entrevues et des questionnaires. Bien que produisant des renseignements utiles de telles études sont onéreuses en termes de ressources et de temps et donc peu susceptibles d'être reproduites fréquemment. Les registres de débarquements commerciaux et les systèmes de surveillance des navires (SSN) fournissent pour leur part des sources d'information continue pouvant être utilisées pour examiner les variations des réseaux de navires au fil du temps. Nous avons utilisé des données de SSN pour définir des réseaux d'associations entre navires. Des relations ont été relevées entre des paramètres de réseaux courants et la performance annuelle basée sur les données de débarquements. Les associations entre navires ont été examinées de plus près en tant que fonctions de l'activité annuelle de la performance des espèces privilégiées et du port de débarquement en utilisant des modèles de graphes aléatoires exponentiels temporels. Nous avons examiné la dynamique des réseaux au fil de 4 années consécutives. Les variations des associations de navires sont clairement reliées à la performance au port de débarquement et aux espèces ciblées. La structure des réseaux pourrait avoir une incidence sur la relation entre les prises et l'effort nominal influençant ainsi les évaluations de stocks et les réactions aux mesures de gestion. Notre méthodologie offre un outil permettant de suivre les variations des réseaux et cerne des situations nécessitant des études plus détaillées. [Traduit par la Rédaction]

Introduction

The popularity of network analysis in fisheries and fish biology has increased in recent years with both the increased profile of network studies in daily life and greater accessibility of software tools to implement it. Networks have been applied to diverse aspects of fishery systems, including marine food webs, spatial connectivity, and fisheries governance (Gaichas and Francis 2008; Drake and Mandrak 2010; Fliervoet et al. 2016). Network analyses have been used across scales, from studying angler movements among reservoirs (Martin et al. 2017) to linking the many dimensions of fisheries (environmental, ecological, sociological, economic, and management) under a common analytical framework (Zador et al. 2017). However, network structure and its change is not typically incorporated in catch standardizations in fisheries science (Maunder and Punt 2004), likely due to a lack of longitudinal relational data among fishing vessels in most commercial fleets. In this study, we are interested in the potential of forming meaningful network models from commercial fisheries data that are related to vessel performance derived from landed catch. If possible, this would provide the potential to incorporate network relationships more broadly in the fisheries statistics used to follow changes in fish populations.

Networks among fish harvesters are often associated with information exchange and potential cooperative behaviour (Barnes et al. 2017; Alexander et al. 2018). Cooperation is more likely when the ratio of benefits to costs exceeds some threshold (Nowak 2006). The tendency to cooperate is not fixed, but can change with environmental conditions or other external factors. In fisheries, benefits will vary with fish abundance and prices, while costs can change with weather conditions, fuel prices, or regulatory conditions. For example, increased fuel costs could limit the range of vessels, concentrate fishing activities, and reduce the benefits of sharing fishing success from individual fish discoveries. Cooperation among fishers can serve several purposes. It may result in better informed fishing decisions that increase fishing success, may

Received 10 October 2019. Accepted 16 January 2021.

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reduce the risk of loss of life, or share the risk of poor returns (McGoodwin 1979; Acheson 1981; Wilson et al. 2013). In the application of fishing effort, cooperative exchanges of information about current fish location is paramount (Wilson 1990).

Information networks in fishing fleets have been examined from both theoretical and empirical perspectives. Little et al. (2004) used a model of the common coral trout (*Plectropomus leopardus*) fishery on the Great Barrier Reef to examine the effect of a Bayesian information sharing network on expected trends in fish catch and abundance. They found that when vessels exchanged information the catch was expected to be higher and fish biomass reduced. They further predicted less variation in annual catch and profit among the vessels. Mbaru and Barnes (2017) employed network analysis to identify key individuals (information brokers) in Kenyan fishing communities for the dissemination of conservation information among six fishing communities. In fisheries governance, the importance of brokerage between scientists and decision makers has been demonstrated through network analysis (Cvitanovic et al. 2017). However, among fish harvesters, brokers can experience reduced performance when they are known to share information across social boundaries. Barnes et al. (2016) found reduced revenues among brokers connecting ethnic groups in a Hawaiian longline fishery.

Social networks have been successfully constructed by questionnaires and linked to fishing success in salmonid (*Oncorhynchus*, *Salmo*, and *Salvelinus* spp.), lobster (*Homarus gammarus*), and bigeye tuna (*Thunnus obesus*) fisheries (Mueller et al. 2008; Turner et al. 2014; Barnes et al. 2017). Yet, constructing social networks from surveys and interviews can be time-consuming and subject to nonresponse biases. Furthermore, relationships among fish harvesters can change through time. Networks constructed from data routinely collected in fisheries would greatly extend the potential application of network analysis in fisheries science and allow their structure and changes to be more easily examined.

The main goal of this paper is to determine whether vessel association networks constructed from routinely collected fisheries data can be meaningfully related to vessel performance. The networks will be based upon vessel proximity while fishing. Performance will be defined using a catch standardization that incorporates time of year, as well as fishing effort and vessel characteristics. To this end, we employ generalized additive mixed models (GAMMs; Wood 2017) to provide an index of vessel performance, classic network metrics, and correlations to identify general trends (Newman 2018), and temporal exponential random graph models (TERGMs; Leifeld et al. 2018) to study the dynamics in networks of vessel associations in relation to vessel performance while accounting for other spatially and behaviourally relevant covariates.

Methods

Fishery overview

Our study examined the Dutch offshore beam trawl fishery from 2007 to 2010 (Fig. 1). We restricted our analysis to fishing activities occurring at least 12 nautical miles (1 n.mi. = 1.852 km) from the coast and outside of the regulatory "Plaice Box". These "offshore" vessels are typically larger and excluded from inshore waters. (Pastoors et al. 2000; Beare et al. 2013). The three sources of data used were the commercial landing records, the vessel monitoring system data (VMS; Gerritsen and Lordan 2011; Hintzen et al. 2012), and the monthly price for each species. Data were obtained from the onsite records of Wageningen Marine Research (P.O. Box 68, 1970 AB IJmuiden, the Netherlands) and online government sources.

Commercial landing records were provided by every vessel for each trip. They included a trip identifier, the date of departure and return from each trip, the port where fish were landed, the quantity (by weight) of species caught each day, and the location (International Council for the Exploration of the Sea rectangle; ICES 1977) where the catch originated. Ports with fewer than six vessels landing catch were not uniquely identified in our data to maintain anonymity of the vessels. The species from the fishery that were available in the landings records were brill (*Scophthalmus rhombus*), Atlantic cod (*Gadus morhua*), plaice (*Pleuronectes platessa*), sole (*Solea solea*), turbot (*Scophthalmus maximus*), and whiting (*Merlangius merlangus*). Sole and plaice are known to be current target species within this fishery and together made up over 87% of the reported landed weight, while turbot remains a high-valued species caught less frequently (Gillis et al. 2008).

The VMS records are automatically reported by vessels at sea, integrating navigation information and satellite communication to provide real-time monitoring of vessel location from shore. In addition to its regulatory function, this also augments existing vessel safety protocols. Records are reported approximately every 2 h and consist of vessel and trip identifier, date, time, position (latitude and longitude), and speed.

The prices for each species were downloaded from the Statistics Netherlands website (CBS 2019). They were calculated from the monthly average of auction prices of fresh fish landed in Dutch ports. The original source of these data was Productschap Vis (the Dutch Fish Product Board).

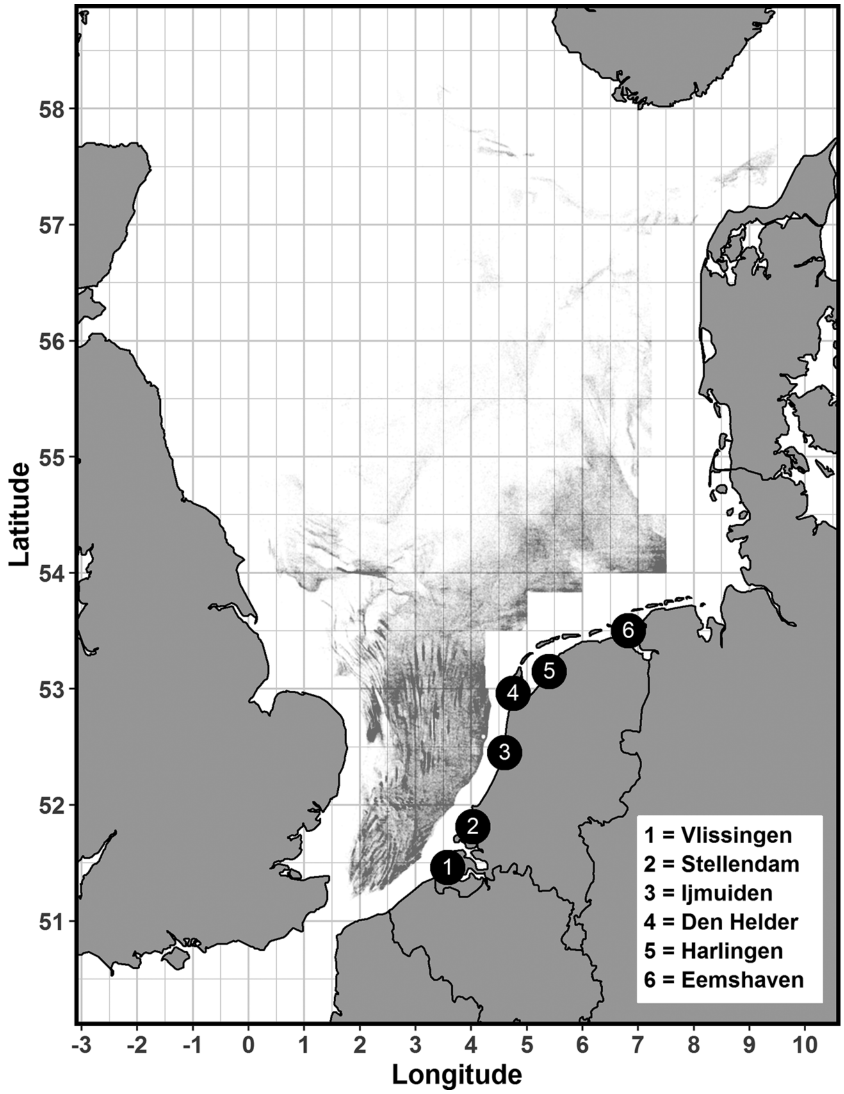
Estimating vessel performance

Vessel performance was derived from the total landed catch throughout the year. To make it comparable among vessels, it must also account for the amount of fishing (gear deployment), local differences in travel costs, potential variation in the availability of fish through the year (due to changes in fish aggregations and movement), and vessel characteristics. We defined a metric of vessel performance based upon standardizing the catch reported on the trip landing records using GAMMs (Wood 2011; Zuur 2012). Each calendar year was standardized separately to match the subsequently constructed annual association networks (see below). This, and all subsequent analyses, were performed using R and its statistical packages (R Core Team 2018). The logarithm of catch was used as the response variable to better approximate normality. The predictor variables were the number of days with reported catch at sea (fishingDays), the number of days at sea without reported catch (otherDays), standardized (Z-scored) horsepower (std_hp), the interactions of std_hp with fishingDays and otherDays, a smooth of the day-of-the-year (1 January = 1) for the start of the trip (s(dateout)), and a smooth representing the random effect of vessels (s(vessel)). The terms fishingDays and otherDays represented nominal effort (in days^{-1}) and days traveling without fishing, respectively. The std_hp term represented potential size- and gear-related vessel differences typically incorporated into standardizations. The interactions allow for differences in catch rate and travel efficiencies with vessel size and gear. The s(dateout) term allowed for temporal (seasonal) variation in catch through the year due to changes in availability from factors such as dispersal or changing habitat as well as the balance of mortality and recruitment. The s(vessel) term used regression splines to estimate simple random effects (Wood 2017; also see R documentation for mgcv::random.effects) that allowed for differences among vessels unrelated to std_hp. Finally, the similarity between consecutive trips was incorporated as a first-order autoregressive term (AR1). This was estimated from the residuals of the GAMM without autocorrelation and then added into a second GAMM estimation using the bam() function of the mgcv package (Wood 2017). The annual vessel performance estimates were extracted from the final model as the random effect values (for annual performance). The standard deviation of the model residuals for each vessel was used to represent variation in a vessel's performance.

Network construction

Unlike social networks constructed from observed communications or surveys of fish harvesters (Mueller 2008; Turner et al.

Fig. 1. Offshore trawl positions of the Dutch beam trawl fleet used in the analysis. The numbered locations are landing ports. Local trawl intensity is indicated by the strength of the shading, with individual trawls plotted as transparent grey points. The coastlines and landforms were taken from the rworldmap and rworldxtra packages of R.



2014; Barnes et al. 2017), our networks of vessel association were constructed from the automated VMS records collected from each vessel throughout a calendar year. This was performed in four steps: (*i*) identifying VMS records associated with trawling, (*ii*) determining the number of other vessels trawling in proximity to each VMS position recorded (simultaneous adjacent trawls), (*iii*) defining associations between vessels (edges in graph or network theory; Newman 2018) based upon their number of adjacent trawls, and (*iv*) constructing an R network object for analysis.

The VMS records were used both to select offshore records and to identify trawls. Only records that occurred outside of the Plaice Box and at least 12 n.mi. beyond the coastline were retained for analysis. All distances were calculated as great circle distances using the haversine formula (distHaversine()) in the geosphere package (Hijmans 2019). Records were classified using their speeds in normal mixture models estimated with the mixtools package (Benaglia et al. 2009). Speed was modeled as a mixture of two normal distributions. An initial mixture was determined using all offshore speed values for the study year. The means of each of these distributions were used as initial estimates in subsequent mixture models that were fit to the records of each vessel separately. This allowed for variation in trawling speed among vessels. Finally, trawling records were defined as records that had speeds within 2 SD of the lower mean from the model. Typically, trawling speeds were ~4–6 n.mi.·h^{-1} and the higher means ("steaming" speed) were ~11–13 n.mi.·h^{-1}. The trawling speeds are on average slightly slower than those found in a previous study (6.6 n.mi.·h^{-1}; Poos et al. 2013) but are based on more recent years and a larger, more diverse set of vessels. Only VMS records classified as trawls were retained for subsequent analysis.

Associations (edges) between vessels were based upon the number of times their VMS trawling records were in close proximity. Calculations were expedited by using R's foreach and associated packages for parallel computing (Microsoft and Weston 2017). For each VMS trawl record, all other records within a 32 km radius and a 24 h period (12 h before and after the record) were determined using distHaversine() (i.e., associated trawl positions). These ranges were chosen to represent the potential for vessel interaction while fishing, based upon expected observability of vessels and the geometry of fishing grounds. 32 km is the distance across which two observers who are both 17 m (56 ft.) above the water would be expected to see each other under ideal viewing conditions (see table 13 in Bowditch 2002). The exact distance will vary with vessel sizes and observer locations (bridge, masts, radar versus visual, etc.). Additionally, this definition was consistent with a previous investigation into the spatial and temporal aspects of localized fishing by North Sea beam trawlers (Rijnsdorp et al. 2011). They found that elliptically shaped fishing grounds were ~17 n.mi. long, based upon tow midpoints. They also found that 80% of the observations were located on local grounds for less than 24 h. Our definition provides a useful first approximation for our analysis. The actual range and time period of vessel interactions will likely vary from our assumptions, even within the Dutch fleet. Interactions that require direct observation would likely happen over a shorter range of distances and times. Alternatively, interactions that result from sharing information about successful trawling locations, such as by radio, may have larger spatial and temporal spans. We account for this by employing a robust definition of associations, described below. The number of associated positions among all vessels were tallied across the entire calendar year to create a matrix of associated trawl position counts representing spatial vessel interactions.

Two transformations converted the associated trawl position count matrix into a network adjacency matrix (Luke 2015; Newman 2018). First, the proportion of tallies attributed to each of the other vessels was calculated for each vessel. These proportions formed the proportional adjacency matrix. This was then transformed into a binary network adjacency matrix by setting all proportions greater than the 95% quantile value to one and all others to zero. These calculations emphasized the strongest associations among vessels in the networks analysed. By focusing on the proportions, rather than absolute counts, and by using the 95th percentile as the threshold, rather than a fixed value, our definition of association will be robust across a range of distances and time periods. This could break down at extremes where either all vessels are equally connected (whole North Sea across many days or weeks) or when counts of co-occurrences between associating vessels are entirely lacking due to highly restrictive criteria. By choosing criteria consistent with previous analyses in our fishery, we have avoided those extremes in our study.

Once the annual adjacency matrix was defined, an R network object was created using the network() function from the statnet collection of packages (Handcock et al. 2008). This resulted in an undirected network with vessels as the vertices and edges (valued 0 or 1) representing the strongest associations. It defined a simple (not bipartite) network that lacked loops (vertices did not link to themselves). Within the network, vertices were assigned attributes that distinguished them in the original data: number of observed trawl positions, species targeting, most common landing port, performance, and variation in performance. We limited our network analyses to vessels that were active throughout all 4 years studied to focus on changes in their relationships through time.

Network overview

The resulting annual networks were visualized using Fruchterman–Reingold network diagrams (Butts 2008). They were quantitatively explored using whole network metrics: number of components, number of isolates, connectedness, edge count, and density (Krackhardt 1994; Newman 2018). The components are groups of vertices that are interconnected by edges. Isolates are the number of vertices without connections to any others. Connectedness is defined as the proportion of all pairs of vertices (dyads) that are connected through one or a series of edges. Finally, the density of the network is the proportion of all possible edges that are present. We have no specific a priori hypothesis about the variation in whole network metrics among years. However, all of the metrics reflect the potential for information exchange that is often proposed in network studies (Granovetter 1983; Krackhardt 1992). The number of distinct components, isolated vessels, and connectedness (proportion of vessel pairs that can reach each other through the network) provide an indication of how freely information either has flowed or could flow in the defined network. However, our selection of only the strongest (upper 5%) associations to form our dichotomous networks limits the conclusions that can be drawn when comparing metrics among years, especially regarding density and edge count. The relationship between general network structure and covariates is more revealing.

The influence of categorical covariates on network structure was examined through network modularity. This measures the tendency for similar vertices with the same covariate values to associate (Newman 2018). Such associations are more generally termed homophily (Goodreau et al. 2009; Newman 2018). The three covariates examined in this manner were the number of VMS trawl observations, the proportion of sole in the landings, and the landing port. These represented the activity level, the fishing strategy, and the community and region where fishing occurred. The number of observations and proportion of sole were made categorical by dividing them into three groups defined by the 1/3 and 2/3 percentile values. More active vessels could be more likely to form associations, even by chance, which should be considered when evaluating other relationships. Pursuing similar species could bring vessels together more often, as could the exploitation of fishing opportunities in the same geographical region. Finally, the landing port itself could provide an opportunity to share information (Gatewood 1987; Palmer 1991) that would result in associations on the water. The null hypothesis for each covariate was estimated by randomizing its value among network vertices and recalculating network modularity. This was done 10 000 times to estimate 95% confidence intervals for the null hypothesis. However, potential collinearities among the covariates makes these single tests descriptive and exploratory rather than establishing strong hypotheses tests (see the following application of TERGMs).

Comparison of each vessel's network metrics with annual performance

The relationship between each vessel's position in the network was compared with its performance (value and variation, see above) using vertex metrics of centrality: degree, betweenness, and eigenvector centrality. Degree is the number of edges connecting a vertex to others. Betweenness measures the number of shortest paths between other vertices that pass through a vertex. Eigenvector centrality is related to a vertex's connections to other vertices of high degree. We expect that greater centrality reflects better access to information within the fleet and the potential to increase vessel performance. Vessels with higher degree have direct associations with more vessels and possibly can draw on a larger information pool. Eigenvector centrality reflects connections to other individuals of high degree (Newman 2018). Vessels scoring highly on this metric may have access to information from other well-informed (connected) vessels even when they have fewer connections in the network overall. Vessels with high betweenness are potential intermediaries or "brokers" between different network components (Robins 2015). This could reflect their location on pathways of potential information flow between distinct groups of vessels. Access to more diverse information sources could improve performance, though poor relationships between the groups being bridged could result in the opposite trend (Barnes et al. 2016).

A permutation test was used to examine the centrality–performance relationships in each of the 4 years. First, a Pearson correlation coefficient was calculated from the observed data. The performance values were then randomly reassigned to each vertex, and the correlation with the network metric was recalculated. This was repeated so that 10 000 correlation values were generated, including the observed value. The position of the observed value in the distribution of simulated and observed values was used to define the two-tailed probability of obtaining the observed value under the null hypothesis (Manly 2007).

Predictors of vessel association

The influence of performance and other covariates on network formation was investigated using temporal exponential random graph models (TERGMs; Leifeld et al. 2018). TERGMs are an extension of ERGMs (Luke 2015) that follow network changes (dynamics) through a series of consecutive observations of network structure (waves). They determine the effect of covariates in a format similar to logistic regression where the response is the probability of an edge existing between two vertices. TERGMs allow a wide variety of covariate definitions, including structural aspects of the network itself and temporal covariates that can span one or more time steps. In this way they can account for the dependent nature of observations from the network when determining the significance of specific predictors. For n vertices, TERGMs predict the probability of an observing a network represented by the $n \times n$ adjacency matrix $\mathbf{N}$, where $N_{ij} = 1$ when vertices i and j are connected and 0 otherwise. Following Leifeld et al. (2018) for a network that is dependent on its configuration in the previous time step, this can be stated as

$$(1) \qquad P\left(\mathbf{N}^t | \mathbf{N}^{t-1}, \quad \boldsymbol{\theta}\right) = \frac{\exp\left[\boldsymbol{\theta}^{\mathrm{T}} \cdot h\left(\mathbf{N}^t, \mathbf{N}^{t-1}\right)\right]}{c(\boldsymbol{\theta})}$$

where $\mathbf{N}^t$ and $\mathbf{N}^{t-1}$ are the current and previous network configurations (waves), $\boldsymbol{\theta}$ is a vector of model coefficients, T is the transpose operator, and $h(\mathbf{N}^t, \mathbf{N}^{t-1})$ is a vector network statistics and covariates. These statistics may be calculated from the conditions at t, at $t - 1$, or across both times. The model can be expanded to include a longer series of networks (waves) and dependencies across more than two consecutive waves. The endogenous network statistics are calculated from the network structure and can include values such as a vertex's number of edges (degree) or shared connections between two vertices to a third vertex (shared partners). The exogenous covariates can be based on vertex or edge attributes. Finally, $c(\boldsymbol{\theta})$ is a normalizing constant representing all possible edge configurations for the number of vertices in the network. The probability of observing a particular sequence of networks is the product of the probabilities of each network in the series, assuming conditional independence (Leifeld et al. 2018).

Within this framework, the probability of a specific edge between vertices i and j (π_{ij}) can be expressed as

$$(2) \qquad \pi_{ij} = \mathrm{P}(N_{ij} = 1 \,|\mathbf{N}^t_{-ij},\, \mathbf{N}^{t-1},\, \boldsymbol{\theta}) = \mathrm{logit}^{-1}\left[\sum_{r=1}^{R} \theta_r \cdot \delta_r^{(ij)}\left(\mathbf{N}^t, \mathbf{N}^{t-1}\right)\right]$$

where the inverse logit function is defined as

$$(3) \qquad \mathrm{logit}^{-1}(x) = \frac{1}{1 + \exp(-x)}$$

and $\mathbf{N}^t_{-ij}$ is the structure of the network at time t considering all possible edges except the one between i and j. $\delta_r^{(ij)}\left(\mathbf{N}^t, \mathbf{N}^{t-1}\right)$ is the change in value of the rth network statistic in the vector when the edge between i and j is toggled between presence and absence ($1 \rightarrow 0$) in $\mathbf{N}^t$, which may depend on $\mathbf{N}^{t-1}$. θ_r is the coefficient in the TERGM associated with the rth network statistic from the $\boldsymbol{h}$ vector of network statistics in eq. 1. See Leifeld et al. (2018) and Morris et al. (2008) for more detail on the model's development and notation.

ERGM (and the derived TERGM) formulations allow for increasingly complex network representations (Goodreau et al. 2009; Harris 2013). When the network statistic in $h(.)$ is only the number of edges (with coefficient θ_{edge}), this model represents a simple random graph — the classic Erdös–Rényi model (Newman 2018). θ_{edge} can also act as a constant term in more complex models. When only exogenous terms are added to the model, it is termed "dyadic-independent". In this model the probability of edge formation is independent of all other edges and is equivalent to a logistic regression of edge presence or absence. The addition of endogenous terms, drawn from the structure of the network, recognizes that the formation of an edge can be dependent on the presence of, and patterns among, neighboring edges. These form "dyadic-dependent" models that require Markov chain Monte Carlo (MCMC) methods to estimate their maximum likelihood solutions (Morris et al. 2008). Additionally, in TERGMs the endogenous terms can be calculated across networks going back through time as well as within the current network.

Our TERGMs of the Dutch North Sea beam trawl fishery attempted to predict the association of vessels (network edges) from vessel covariates (exogenous) and network structure (endogenous), including network stability through time. This combined the networks of all years studied into a single analysis. We limited ourselves to main effects due to the number of vessels observed (77 vessels active across all 4 years) to estimate 25 model coefficients. Collinearity among the exogenous predictors was examined using generalized variance inflation factors (GVIF; Fox 2015).

The continuous vessel covariates were the number of trawling observations (nObs) of each vessel (its activity level) during the year and their performance represented by the random effect from the earlier GAMM (performance). Both of these covariates were standardized to mean zero and unit variance to allow the relative impact of their effects to be directly compared. The number of observations of a vessel's fishing position could influence the probability of detecting associations, such that vessels that were at sea more would have a greater opportunity to be near others. We wished to account for this effect before drawing conclusions about other covariates. Performance is expected to increase the probability of edge formation since associating with successful vessels at sea is an obvious way to attempt to enhance catch.

Qualitative vessel covariates (factors) were general fishing strategy (pSOL) based on the proportion of sole in the annual catch and the most common landing port (landing port) during each year studied. For pSOL, three categories (low, medium, and high) corresponded to the three equally sized quantiles (1/3, 2/3, 1) of the distribution of the proportion of sole in the annual landings. Differences in the concentration or behaviour of the species pursued could impact the proximity of fishing vessels. Similarly, the fishing grounds in the vicinity of each port may differ in the local distribution of fish and impact vessel proximity while fishing.

After accounting for classic main effects, performance, pSol, and landing port were also examined for the tendency of similar vessels to associate. For pSol and landing port, homophily (Goodreau et al. 2009) was directly examined. For performance, we tested heterophily, the increased tendency for more different vessels to be associated, by examining the absolute difference in performance measures between vessels. These tests relate to assortative associations based on fishing success, fishing strategies, and possible geographic influences or constraints. Fishers on more successful vessels may be reluctant to share information with less skilled or inexperienced fishers who may be unable to reciprocate. Pursuing similar species or fishing opportunities in the same regions could contribute to vessel segregation. Finally, sharing information within ports could also result in vessel associations on the water.

The influence of local network structure (endogenous effects) was represented by the geometrically weighted degree distribution (GWD) and the geometrically weighted edge-wise shared partners statistic (GWESP) (Hunter 2007; Goodreau et al. 2009). Failing to account for these could bias the examination of other coefficients by treating dependent edges as independent in the analysis, akin to pseudoreplication in ecological studies (Hurlbert 1984). However, the main purpose of these coefficients is to test for the influence of social interactions on the formation of new associations within a network. GWD examines the effect of network centralization on the formation of new edges (Levy and Lubell 2018). It quantifies the centralization of the network in terms of the number of edges connected to each vertex. In our fishing networks this would distinguish between a tendency in vessel associations toward more centralization (following a leader, for example) and more diffuse arrangements (possibly avoiding dense clusters). The influence on this statistic of adding an edge to a vertex of lower degree is greater than adding an edge to a vertex of higher degree. The strength of this tendency is determined by an exponent (decay coefficient). GWESP quantifies the effect of existing edges to a common vertex (partners) on the probability of forming an edge between those two vertices, forming a triangle pattern (closure). Common partners could enhance the probability of forming a new association through social factors such as a greater ease in initial introductions or perceived trustworthiness in those that have existing relationships with other trusted partners (Goodreau et al. 2009). With GWESP the effect of each additional shared partner on the formation of an edge is not linear, but declines as the number of partners increases. The rate of this decline also varies with an exponent. These statistics are more complex than the simple degree and triangle statistics that preceded them in network analysis, but they produce network solutions that have better MCMC convergence properties than the former measures (Hunter et al. 2008). With simple networks the decay coefficients may be estimable, but in more complex models like ours this can also result in failure of MCMC convergence. In our case they were fixed (1.0 for GWD and GWESP). The sensitivity of the assumed values was investigated by repeating the analysis around those values. Only the results using an exponent of one are presented due to their insensitivity to its value.

To examine the role of different types of covariates in our networks, we compared several models of increasing complexity, beginning with a simple random graph (Erdös–Rényi model network). Subsequently, we examined networks that incorporated — temporal network stability, endogenous effects, exogenous effects, and all effects combined. Stability represents potential social inertial across time — the tendency for associations among vessels, or their absence, to be maintained. Endogenous effects allow the role of social interactions based upon existing levels of interaction (number of other associations) and closure (closing triangles with shared partners). In our models the exogenous factors are characteristics of the vessels that are independent of network structure. Finally, the full model combined all of these potential influences. The final model was selected from among these using the criteria of area under the precision-recall curve (AUC-PR).

AUC-PR provided an index of model fit that was based upon the successful prediction of edges in the network (Leifeld et al. 2018). In our study, precision was calculated as the number of correctly predicted edges divided by the total number of predicted edges in the network; this estimates the probability of a predicted edge existing. Recall estimates the probability of an existing edge being predicted and was calculated as the number of correctly predicted edges divided by the number of edges in the network. Typically, when precision is plotted on recall it declines as recall increases. However, better models maintain higher precisions through increases in recall, tending towards a horizontal line near a precision of one. As both precision and recall vary between zero and one, the area under this curve approaches one as the quality of the model increases. In contrast, a random model would result in a horizontal line at a precision equal to a simple probability of an edge forming. A more detailed development of precision-recall curves and their use in model selection can be found in Davis and Goadrich (2006). Pursuing a single metric can lead to overfitting and requires additional model evaluation.

Table 1. Overview of offshore Dutch beam trawl fishery data used in this study.

	2007	2008	2009	2010
Effort				
Vessels	111	101	84	82
Trips	4 833	3 678	3 778	3 733
Total days	20 842	15 660	16 239	16 171
Unique days	361	360	360	362
Unique rectangles	84	75	70	78
Trawling positions	220 680	166 971	178 740	164 924
Catch weight (kg)				
Sole	8 630 838	7 889 951	8 066 712	7 210 357
Plaice	20 400 926	16 592 445	19 415 917	22 384 679
Turbot	1 926 325	1 436 704	1 423 449	1 258 278
Others	3 316 437	2 695 634	3 088 221	3 147 540
Catch value (€)				
Sole	64 741 572	70 124 370	58 641 859	46 420 850
Plaice	57 950 049	46 294 903	47 083 866	56 542 539
Turbot	3 957 194	2 738 756	1 972 968	1 680 051
Others	18 538 315	17 916 475	20 403 300	25 936 734

Note: Effort is described by the number of vessels, trips, reported days fishing, and the number of trawling positions identified from the vessel monitoring system (VMS) data. The number of unique days and International Council for the Exploration of the Sea (ICES) rectangles represent the temporal and spatial extent of the fishery in each year. Catch for the three most valuable species and others combined is reported both as weight and value landed.

The goodness-of-fit of the final model was examined in more detail using the graphical methods of Hunter et al. (2008) and Leifeld et al. (2018). These compare the distribution of network statistics in the observed data with those constructed by simulating networks based upon the estimated TERGM. The network comparisons examined the degree distribution, dyad-wise and edge-wise shared partner distributions, triad census, and the distribution of minimum geodesic distances among all vertices. Ideally, we expect the observed statistics to fall within the range of those calculated from the simulated networks.

Though the TERGM described above represented temporal dynamics, it did not explicitly address the question of whether performance (standardized fishing success based on catch) drove network formation or was positively influenced by it. To probe this more directly, we considered an alternate covariate, the performance from the previous year. The lagged and unlagged performance covariates were highly correlated ($r > 0.87$ in adjacent years), which could result in collinearity issues if both were used in a single model. Therefore, we compared the model using lagged performance with the model using current performance.

Results

Fishery overview

The number of vessels participating in the offshore fishery declined through the 4 years examined, but the number of trips and total days reporting fishing remained similar after an initial drop following 2007 (Table 1). The number of days where fishing was reported by at least one vessel was high (≥360 days) for all of the years examined. The number of ICES rectangles (30′ latitude × 1° longitude; ICES 1977) reporting catches declined during the first 3 years, but then increased in 2010. The number of VMS positions classified as trawling by our analysis was greatest in 2007. Plaice had the greatest landed weight among all of the years examined, while sole landed the greatest value in the first 3 years, declining over the last 3 years. The variation in market conditions was demonstrated in 2008, where the greatest value of sole landed corresponded to the second lowest quantity of sole landed.

The location of fishing trawls (VMS records) in the offshore portion of the Dutch beam trawl fishery are shown in Fig. 1. The VMS trawls followed the boundary of the Plaice Box (Pastoors et al. 2000; Beare et al. 2013) clearly in the northeast. Concentrations of fishing activity were greatest in the south, and the effects of bathymetry on trawling locations were also evident (see van der Reijden et al. 2018 for a more detailed discussion on bottom types). Fishing from the main ports studied (six or more vessels) was not spatially uniform across the whole area fished (Fig. A1). Vlissingen fishing was concentrated in a small area between the Straits of Dover and 52°N. Stellendam's activities were mostly south of 53°N. Vessels from IJmuiden fished further north, in some cases off Norway, but mostly below 54°N. The Den Helder vessels were also mostly active below 54°N, but followed the edge of the Plaice Box more closely. Harlingen trawls were concentrated on either side of 54°N and were bounded strongly by the Plaice Box. Eemshaven trawls were concentrated immediately north of the port, between 54°N and 55°N. There was little notable difference in the overall distribution of trawl locations among the 4 years studied (Fig. A2).

Catch standardization and vessel performance

The number of days fishing and the other days at sea during a trip were the most consistent predictors of catch value (log-transformed; Table 2*a*). Other predictors (standardized horsepower and its interactions) varied in magnitude and significance between years. When significant, catch value was positively related to the number of days fished and the number of nonfishing days in the trip. Significant horsepower coefficients were positive. The interaction of days fishing and horsepower was positive where significant. In contrast, significant nonfishing days × horsepower interactions were negative, indicating an effect of nonfishing days on the catch that declined with smaller vessels. All terms were retained in all models to allow consistent standardization of performance among years.

The smooth terms representing seasonal trends and vessel random effects were both significant in all of the years examined (Table 2*b*). For each of the years the smooth term indicated a midyear dip in total landed value (Fig. 2). The standard deviation of the random effects appeared to increase throughout the study but was also similar in magnitude to the variation observed in the model residuals in each of the years (Table 2*c*).

Network overview

In 2007, patterns in association were geographically related (Fig. 3). The southernmost port (Vlissingen) vessels fished together in a strongly connected network component. Strongly connected components have many direct connections among most or all of their vertices. Stellendam, the next most southerly port, also formed strongly connected groups, but it also had clear associations with vessels from IJmuiden and Den Helder. Vessels from IJmuiden tended to associate with other IJmuiden vessels and those from Den Helder, though a Stellendam group (right of center) was situated between two IJmuiden groups. Harlingen vessels associated most commonly with vessels from Den Helder and Harlingen, while Eemshaven vessels mostly associated with others from the same port in a strongly connected grouping. The general pattern of association followed the northeast–southwest distribution of ports along the coast. The "other" landing port vessels are scattered throughout the network and represent smaller ports that are not identified to preserve confidentiality.

In subsequent years the association networks generated from the VMS records varied, emphasizing their dynamic nature (Fig. 4). The connectivity within the networks seemed similar initially and then noticeably declined (2009, 2010). The geographical nature of associations was maintained, while more active vessels (larger nodes in Fig. 4) often had more edges. As the network became less connected more "star" patterns (unconnected vertices connected through a central vertex) appeared. The central node was often a vessel with much fishing activity, but in 2010 the large star formation of mostly Harlingen vessels had a single vessel from Den Helder that was more active than the central vessel (Fig. 4, upper left). All of the networks seemed to have a large component with few edges between its vertices (weakly connected). Also, strongly connected Emmshaven and Vlissingen components became more evident as time advanced, and the networks became more fragmented.

Table 2. Fixed effects from generalized additive mixed model (GAMM) catch standardization used to define the vessel performance metric (*a*), GAMM smooth parameters from catch standardizations used to define vessel performance (*b*), and variation in the GAMMs used for catch standardization (*c*).

(*a*) Fixed effects

Year	Coefficient	Estimate	SE	*t*	*p*
2007	(Intercept)	3.870	0.012	320.201	<0.001
	fishingDays	0.129	0.002	68.683	<0.001
	otherDays	0.065	0.003	23.311	<0.001
	std_hp	0.011	0.013	0.837	0.403
	fishingDays × std_hp	0.014	0.002	5.712	<0.001
	otherDays × std_hp	−0.008	0.003	−2.836	0.005
2008	(Intercept)	3.957	0.014	274.096	<0.001
	fishingDays	0.119	0.002	55.047	<0.001
	otherDays	0.065	0.003	20.581	<0.001
	std_hp	0.084	0.015	5.593	<0.001
	fishingDays × std_hp	−0.001	0.003	−0.384	0.889
	otherDays × std_hp	−0.017	0.003	−5.371	<0.001
2009	(Intercept)	3.855	0.017	224.461	<0.001
	fishingDays	0.137	0.003	50.850	<0.001
	otherDays	0.068	0.004	18.751	<0.001
	std_hp	−0.018	0.017	−1.062	0.288
	fishingDays × std_hp	0.026	0.003	8.125	<0.001
	otherDays × std_hp	−0.003	0.004	−0.833	0.405
2010	(Intercept)	3.915	0.018	216.607	<0.001
	fishingDays	0.126	0.003	48.671	<0.001
	otherDays	0.071	0.004	19.972	<0.001
	std_hp	0.111	0.020	5.430	<0.001
	fishingDays × std_hp	−0.005	0.004	−1.335	0.182
	otherDays × std_hp	−0.019	0.004	−4.478	<0.001

(*b*) Smooth parameters

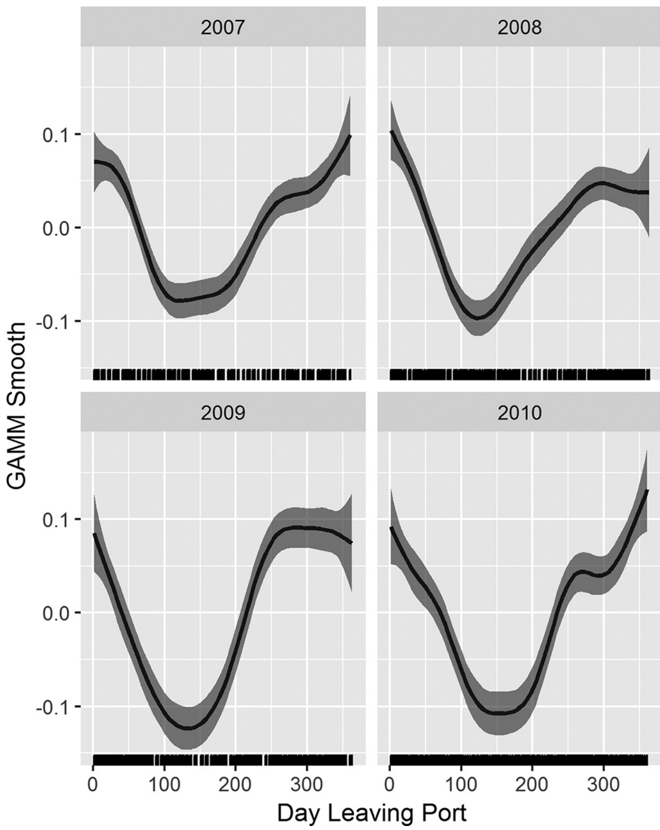
Year	Smooth	Est. df	*F*	*p*
2007	s(dateout)	8.008	113.886	<0.001
	s(vessel)	103.528	17.661	<0.001
2008	s(dateout)	7.455	112.899	<0.001
	s(vessel)	92.789	20.331	<0.001
2009	s(dateout)	7.551	160.563	<0.001
	s(vessel)	78.784	23.116	<0.001
2010	s(dateout)	8.074	123.785	<0.001
	s(vessel)	77.904	35.409	<0.001

(*c*) Variation in GAMMs

Parameter	2007	2008	2009	2010
AR(1)-ρ	0.193	0.145	0.248	0.171
Residual SD	0.099	0.095	0.105	0.105
Vessel RE SD	0.082	0.095	0.101	0.116

Note: (*b*) Seasonal patterns are captured by the smooth of the first day of the trip (dateout), and the random effects for each vessel are estimated by the vessel smooth. Est. df is the estimated degrees of freedom for the smooth. (*c*) For variation in the GAMMs used for catch standardization, the autocorrelation between consecutive trips (AR(1)-ρ) is estimated from the residuals of a preliminary GAMM without autocorrelation and is fixed at the stated value for the final estimation. SD = standard deviation; RE = random effects.

Fig. 2. Smooth components of the catch standardization generalized additive mixed models (GAMMs) for each year. Observations are indicated by the rug plot along the horizontal axis. The smooths are in the units of the linear predictor, which is the logarithm of the value of all species records for each trip.



The differences among years were quantified with network metrics (Table 3). The density of the networks and edge counts followed the same pattern: similar among years but greatest in 2008. The similarity was likely due to their definition based upon the most highly associated vessels (95th percentile). Density and edge count are expected to vary together when networks are the same size, defined here by the vessels active across all years. The number of distinct network components was greatest in the last 2 years, while the number of isolated vertices among the 77 vessels was generally low, greatest in 2009. The overall connectedness was initially high (2007, 2008) and noticeably less in the last years (2009, 2010). Furthermore, the components of the networks were noticeably smaller (fewer vertices) and the networks less connected in the last 2 years, especially 2010 (Fig. 4).

Modularity was significantly related to all of the vertex attributes considered (Table 4). Each coefficient fell outside of the 95% confidence interval constructed for the null hypothesis. This indicates that network structure was influenced by a vessel's landing port, activity (discretized as nObs), and fishing strategy (discretized as pSOL). More insight into these effects was provided by the subsequent TERGMs.

Comparison of each vessel's network metrics with annual performance

The network metrics for vertices (vessels) were found to be related to the vessel's GAMM standardized performance (Table 5) for two of the three metrics examined. Degree and eigenvector centrality were positively correlated with performance in 3 of the 4 years examined. However, betweenness centrality had no discernible relationship with performance in any of the years examined. Vessel network metrics were not significantly correlated with the variation in the vessel's performance (estimated from GAMM residuals), and so these results are not presented.

Predictors of vessel association dynamics (TERGMs)

The model containing all types of predictors provided the best fit as indicated by the AUC-PR curve (AUC-PR mean among years > 0.60; Table 6).The poorest fit was seen in the random network, with a mean AUC-PR among years of $\sim$0.05, reflecting the density of the network. Including the term for network stability improved the predictive ability of the model by 30%. The additional inclusion of endogenous (network structure) and exogenous (vessel characteristics) predictors also improved the model. The addition of exogenous predictors to the stability model resulted in the greatest improvement from random and a $>$0.10 improvement over an alternative addition of the remaining endogenous predictors. The full model, including both endogenous and exogenous predictors, provides an additional improvement of $\sim$0.03.

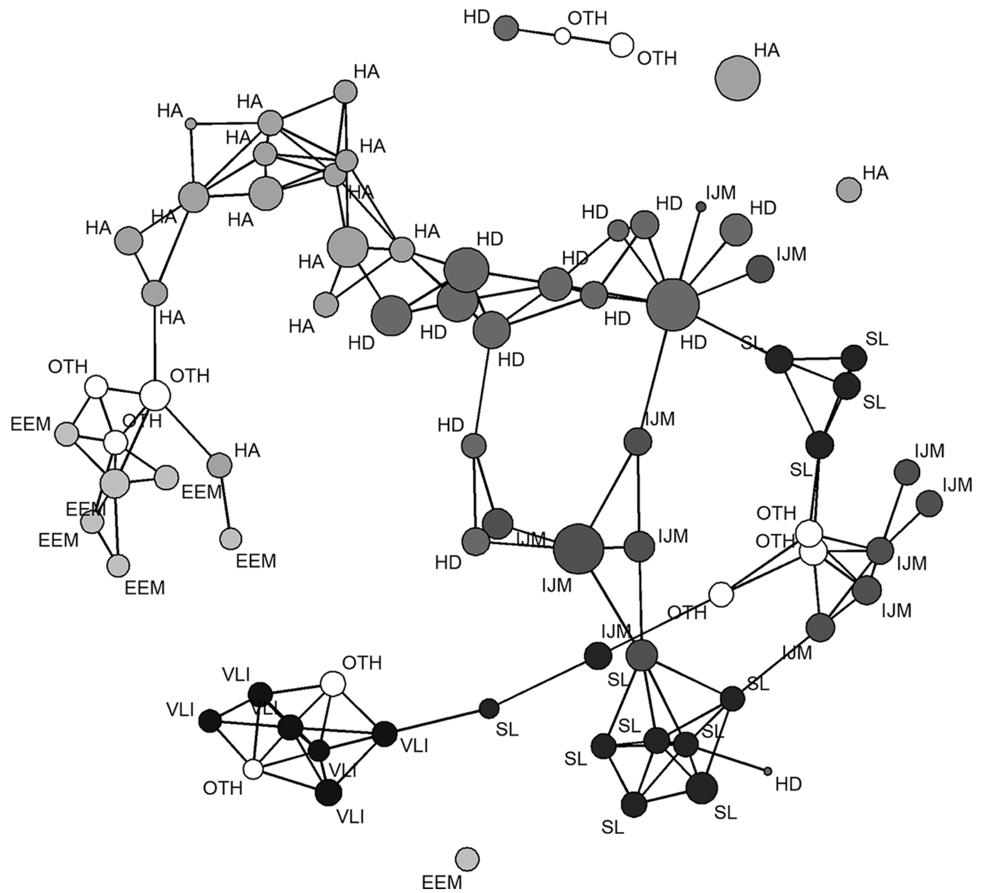
The full model was also modified to examine the effect of including lagged performance metrics instead of their current values (Table 7). This was done to consider the potential for directional causality, such that the performance of the previous year would be the strongest influence on vessel associations within the current year (Leifeld et al. 2018). Ultimately, the model with unlagged performance metrics had the greatest mean AUC-PR value. Therefore, the original full model based upon current performance metrics was used as the focus of our subsequent analysis.

The goodness-of-fit of the selected model was examined prior to further interpretation. The metrics examined were within the range of values expected from our TERGM, with some irregularities within those ranges (Fig. 5). The degree distribution was particularly irregular, but still within the 95% range of the degree distribution expected from the TERGM. More significantly, the distribution of geodesic differences between vertices was fit well, though it was not directly represented in the TERGM, unlike degree and triads, which are related to GWD and GWESP. The final AUC-PR shows that this model clearly outperforms that expected from a random network. More background on interpreting the statistics in these diagnostic plots can be found in Leifeld et al. (2018) and Hunter et al. (2008). Given the quality of the fit, we continued to interpret the model results.

The coefficients of our final TERGM (Table 8) represented the strength of the relationship between the predictors and the tendency for vessels to form associations between consecutive years. Specifically, they quantified the effects of the predictors on the log-odds ratio (logit) of edge formation. The sign of these coefficients indicated the direction of their effects on the underlying probability of a connection between two vertices. All coefficients were found significant and retained in the final model. The MCMC chains displayed good mixing and no signs of degeneracy, with the minor exception of the chains estimating homophily in vessels from Vlissingen, which display some multimodality. Repeating the analysis with a single homophily term eliminated this issue but also yielded similar model results, so the more detailed model was retained. Goodness-of-fit simulations determined that the degree distribution and edge-wise shared partner distribution were within the range of values expected from the final model. The distribution of minimum geodesic distances showed greater departures from the observed values, but the observations were usually within the simulated confidence intervals. No appreciable collinearity was detectable among the exogenous predictors (all $\mathrm{GVIF}^{1/(2\times \mathrm{df})} < 2$; Fox 2015).

The significant endogenous coefficients indicated that internal processes were relevant to network formation across the years examined. The edges term corresponded to a constant probability (expressed as log-odds) of edge formation without covariate

Fig. 3. Vessel association network of the Dutch offshore beam trawl fleet for 2007. Edges (lines) link associated vessels (vertices). The size of the vertex indicates the relative number of observed trawling vessel monitoring system (VMS) records for the year. The abbreviations indicate the most common landing port used by the vessel: VLI = Vlissingen, SL = Stellendam, IJM = IJmuiden, HD = Den Helder, HA = Harlingen, EEM = Eemshaven. The shading of the vertices indicates the relative latitude of the landing port, becoming lighter for more northerly ports. OTH are unshaded circles and represent vessels from ports with six or fewer vessels that were not identified to preserve confidentiality.



effects. The positive temporal stability indicated a tendency for the presence (or absence) of edges to be maintained between adjacent years (waves). The positive GWD statistic indicated that the probability of association for a particular vessel was influenced by connections to other vessels. More specifically, it corresponded to a reduction in edge formation to vertices that already had a large number of edges (i.e., less centralization; Levy and Lubell 2018). The positive GWESP indicated that edges were more likely to form between vertices that were already connected by a third common vertex.

The exogenous coefficients represent the contributions of vertex (vessel) attributes to network formation independent of network structure. Higher numbers of VMS records classified as trawls (nObs) increased the probability of edges to that vessel. This was not surprising, since more activity at sea would increase the probability of encountering other vessels, but needed to be incorporated to remove its effect from the interpretation of the other covariates examined.

The TERGM suggested that vessel performance (standardized catch) strongly influenced the formation of edges, both through its magnitude and homophily. Vessels with greater performance were more likely to form edges in all of the years examined. This effect was more predictive within a year than when considering performance in previous years, as noted previously. Homophily was illustrated through the negative heterophily coefficient. It indicated that edge formation was less probable between more vessels with more disparate performance values.

The probability of edge formation differed with catch composition (representing targeting). Vessels with a high proportion of sole in their landings had a lower probability of forming edges. Vessels with intermediate levels of sole in their annual landed catch had the greatest probability of forming edges, as indicated by the highest targeting coefficient (0.73). The middle targeting category had a negative homophily coefficient, suggesting that edge formation favours connections to vessels with different targeting strategies. The high and low sole vessels both appeared to associate more within their classification.

Landing port influenced the probability of edge formation through both general port tendencies and homophily among vessels using the same port. The main effect on the probability of edge formation was lower than that estimated for Eemshaven in all identifiable ports. Interestingly, the two southernmost ports were closest to Eemshaven in this estimate. Homophily was more strongly related to the formation of new edges in the northern ports (Eemshaven, Harlingen, and Den Helder). Among the more southern ports, it was strongest in Vlissingen.

Discussion

Our analyses established that there was a relationship between networks constructed from vessel associations at sea and their annual performance in the Dutch beam trawl fishery. Simple correlations were revealed between performance and both vessel degree and eigenvector centrality. Vessels that had more associations with other vessels or that were associated with vessels with a greater number of associations tended to have better catches.

Fig. 4. Vessel association networks for each of the years studied. Symbols are the same as Fig. 3, except landing port abbreviations are not shown due to limited space.

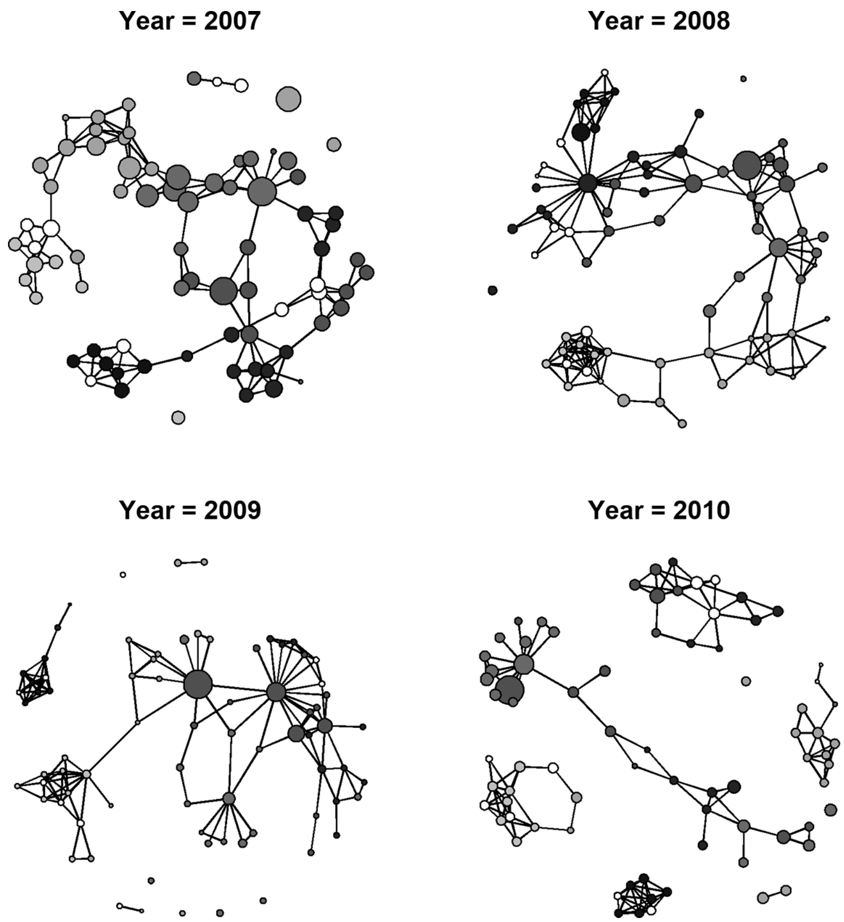


Table 3. General network metrics of annual vessel association networks.

Metric	2007	2008	2009	2010
Size	77	77	77	77
Components	5	3	9	8
Isolates	3	2	5	2
Connectedness	0.850	0.948	0.581	0.206
Edge count	144	171	146	141
Density	0.049	0.058	0.050	0.048

Table 4. Network modularity in relation to vessel attributes.

			H_0	
Attribute	Year	Modularity	Lower 95%	Upper 95%
Landing port	2007	0.529	−0.058	0.034
	2008	0.521	−0.055	0.029
	2009	0.408	−0.060	0.030
	2010	0.473	−0.059	0.032
No. of observations	2007	0.107	−0.070	0.055
	2008	0.079	−0.065	0.047
	2009	0.105	−0.070	0.048
	2010	0.162	−0.072	0.055
Proportion of sole landed	2007	0.308	−0.071	0.054
	2008	0.295	−0.065	0.047
	2009	0.356	−0.070	0.050
	2010	0.272	−0.071	0.054

Note: Network structure is estimated from the observed network attributes, and then for a null model the network is constructed by randomizing the attribute labels 10 000 times to estimate the 95% confidence intervals of the null hypotheses (H_0). The number of observations (nObs) and proportion of sole landed (pSOL) were discretized into three equal categories (low, medium, high) before calculating modularity. For all covariates, the observed modularity values fell outside of the 95% range expected under H_0, indicating significance.

The relationship was further supported by our dynamic network analysis (TERGM) after accounting for landing port, species targeting, and differences in fishing activity among vessels.

Our network correlations were consistent with previous fishery network studies. Turner et al. (2014) constructed a directed network of information sharing in the Northumberland lobster fishery based on survey data. They found that network centrality was positively related to perceived fishing success, though perceived success and actual landings (when available) were only moderately correlated ($r_s = 0.66$; Turner et al. 2014). Mueller et al. (2008) examined the relationship between network position and catch success in the Lake Michigan salmon charter fishery. They found that captains with more reciprocated edges in a directed network had greater success, based upon self-reported monthly average catches. Barnes et al. (2017) were able to compare directed networks developed from structured surveys with revenue data from the Hawaiian longline fleet. They found that in-degree was positively related to revenue on an annual basis, but not within a trip. However, neither our correlations nor these other studies accounted for dyadic dependence in network structure when testing the relationship between centrality and performance.

A relationship between network structure and performance was further supported by our dynamic network analysis (TERGM).

Table 5. The relationship between annual performance (vessel's random effect from the standardizing GAMM) and the vessel's network centrality, using nonparametric correlation with Kendall's tau.

Centrality	Year	ρ	p value
Betweenness	2007	0.037	0.757
	2008	−0.035	0.770
	2009	−0.143	0.213
	2010	0.011	0.894
Degree	2007	0.119	0.302
	2008	0.260	0.024
	2009	0.242	0.038
	2010	0.429	0.000
Eigenvector	2007	−0.308	0.011
	2008	0.114	0.316
	2009	0.463	<0.001
	2010	0.533	<0.001

Note: p values were determined by randomization. After calculating the observed correlation, performance values were randomly shuffled among vessels and Pearson correlation (ρ) was recalculated 9999 times. This estimated the probability of the observed tau under the null hypothesis based upon 10 000 values assumed to come from the same distribution.

Table 6. Model fits with varying model complexity.

	Area under precision-recall curve			
Model	2008	2009	2010	Mean
All terms	0.616	0.521	0.650	0.596
Exogenous and stability	0.604	0.464	0.622	0.563
Endogenous and stability	0.388	0.415	0.545	0.449
Exogenous	0.460	0.370	0.437	0.422
Temporal stability	0.344	0.350	0.401	0.365
Random	0.048	0.066	0.046	0.054

Note: The fit of the model is indicated by the area under the precision-recall curve, strictly positive with a maximum of one. The model consisting of only endogenous predictors is not displayed because it did not converge.

Table 7. Model fits with lags of performance metrics.

	Area under precision-recall curve			
Model	2008	2009	2010	Mean
Current performance and current homophily	0.683	0.521	0.662	0.622
Lagged performance and lagged homophily	0.666	0.510	0.649	0.608
Current performance and lagged homophily	0.675	0.515	0.663	0.618
Lagged performance and current homophily	0.672	0.513	0.660	0.615

Note: Lags of both performance and the absolute difference in performance between vertices (homophily examined as heterophily) were considered. The fit of the model is indicated by the area under the precision-recall curve, strictly positive with a maximum of one.

In addition to controlling for dyadic dependence, we also accounted for landing port, species targeting, and differences in fishing activity among vessels. Overall, we can conclude that network position and processes are associated with fishing success. However, neither direct correlations nor TERGMs established causality — do vessels associate due to performance or do their associations enhance their performance?

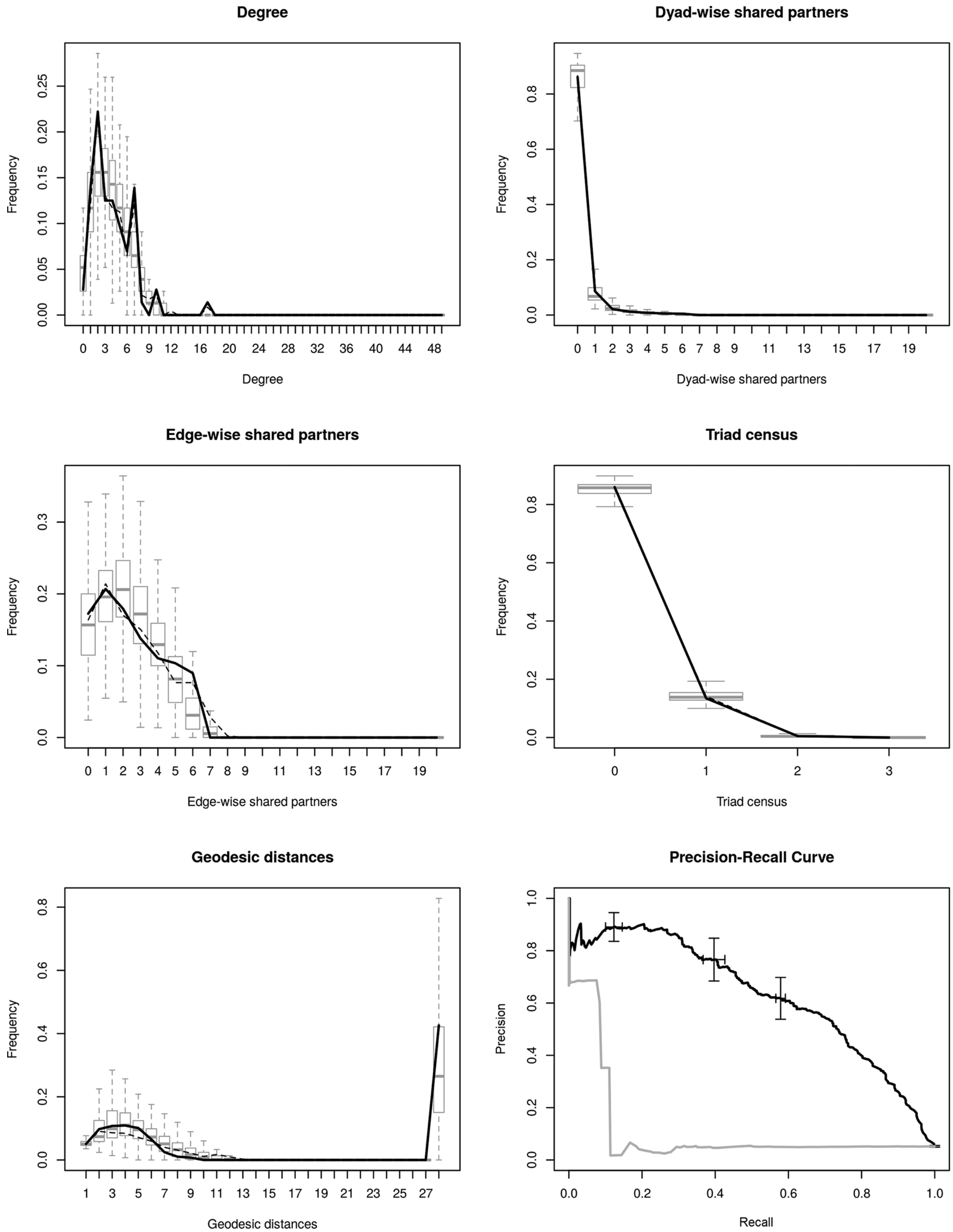
Uncertainty in causality is a common concern in studies based upon observational data. Generally, regression-type models imply Y is caused by X rather than testing it explicitly. Network models add additional complexity by considering how group effects from the network impact individuals who are themselves contributors to those group effects — the classic "reflection problem" described by Manski (1993). Carefully designed manipulative experiments would more clearly establish causality in network studies but these are seldom possible (Wasserman 2013). Robins (2015) discusses the issue of causality in network models in more depth, including other complicating factors such as relevant but unobserved covariates, and the value of models that are only consistent with causality. Ultimately, how we consider causality is limited by the nature of the data at hand.

Using past values of covariates as predictors (Robins 2015; Leifeld et al. 2018) more directly represents causality. This takes advantage of the "arrow of time" — current events do not influence the past. Where a model based upon the past values of a covariate outperforms contemporary values, the hypothesis of causality is strongly supported. Unfortunately, our comparison of TERGM predictors showed the opposite trend. The high correlation in vessel performance between adjacent years further complicates our investigation of causality — we expect similar prediction of edge formation from both lagged and unlagged performances. This may be overcome through a manipulative study that randomized vessels within the network (unlikely to occur). Insight could also come from a novel fishery, followed from its beginnings before associations became established. Such a study should occur when performance-related skills and relationships are first developing. The role of early network formation on current dynamics is clear from the significance of network stability in our TERGM. However, the significance of the other predictors shows that network dynamics (changes between years) are more than just inertia with a random element.

Our TERGM results also indicated that associations were more likely to form among vessels with similar performances (expressed as negative heterophily in the analysis). Preferential associations among individuals with similar characteristics is well established in the social network literature. It can occur by building on groupings that already exist, such as gender or location (Goodreau et al. 2009; Alexander et al. 2018). It may also occur when individuals attempt to limit asymmetry in their interactions (Apicella et al. 2012). In fisheries, correlation between vessel interaction and fishing success has been directly observed (Palmer 1990), so it is not surprising that we see it in our analysis. This result is not simply driven by vessel location or the species pursued, which are both controlled in our analysis. Instead it suggests a deliberate choice by vessel masters and communication among them. A causal alternative is that vessels have highly skillful masters who each have excellent knowledge of fish and vessel distributions. Arriving at the best time and place together could generate spatial associations without direct interactions among them. However, this is less likely than the presence of communication and some coordination in their search for fish, which has long been observed in other fisheries (Andersen 1973; Gatewood 1987; Palmer 1991).

The existence of association networks in fishing activity is not surprising; vessels pursuing aggregated fish (Poos and Rijnsdorp 2007; Rijnsdorp et al. 2011; van der Reijden et al. 2018) are likely to be found in close proximity. Our vessel networks were formed from the strongest associations observed on the water. This was done to emphasize any relationship between associations at sea and fishing success and to avoid creating networks with a single component connecting all vessels. However, a network constructed in this manner may not represent information exchange well. The network literature distinguishes between strong and weak ties (Granovetter 1973). Typically, the maintenance of social structure is

Fig. 5. Goodness-of-fit plots for the final temporal exponential random graph model (TERGM) examining factors influencing the formation of edges (associations) between vertices (vessels) in sequential annual networks of vessels while fishing. The first five plots illustrate the fit of the observed network statistics (solid line) to the distribution of those statistics (box and whisker plots) expected if the TERGM is true. Ideally, the lines should fall within the TERGM's expectations. The sixth plot is the precision-recall curve (black) that indicates the success of the TERGM in predicting edge formation in comparison with a random network (grey). Standard errors are indicated by whiskers around selected points used to construct the TERGM's curve.



attributed to strong ties, while weak ties provide better access to innovative information (Krackhardt 1992). In our case, the information of interest is fish distribution and abundance. We expect that there is a hierarchy to this information. Local fluctuations in abundance due to recent exploitation or fish movements happen constantly. Following them allows vessels to maximize their success by moving in a frequency-dependent manner that is often observed in fisheries (Rijnsdorp et al. 2000; Gillis 2003; Gillis and Van der Lee 2012). Alternatively, and more rarely, the discovery of unexploited fishing grounds, pursuit of new species, or the application of novel gear types represent the type of innovation typically associated with information flow among weak ties (Granovetter 1983). In our model, it is likely that the majority of the information exchanged within a year is "evolutionary rather than revolutionary", tuning and building on existing relationships. Thus, our strong ties are well suited to constructing networks that are relevant to maintaining profits in an established fishery.

We incorporated network structure and vessel properties in the TERGM primarily to control for their effects when examining the relationship between network dynamics and vessel performance. However, these covariates indicated aspects of network dynamics that were insightful in themselves. We were not surprised that more active vessels had a greater probability of forming associations with others; this would be expected even if association was random. The relationships between vessel association and other vessel characteristics are more revealing.

The importance of geography was indicated by the significance of landing port and targeting in both our initial exploration of the annual networks (modularity) and the subsequent dynamic network model (TERGM). Proximity is related to association in many social settings (Rivera et al. 2010), including other fisheries (Alexander et al. 2018), seniors' communities (Schafer 2015), and even online networks that are not obviously constrained geographically (Huang et al. 2013). In the Dutch trawl fishery, masters and crews of vessels sharing a common landing port will have more opportunities to interact on shore and similar access to the surrounding fishing opportunities. The underlying mechanisms of vessel association may be both social (direct communications) or environmental (fish concentrations leading to vessel concentrations). These environmental mechanisms could also arise from pursuing the same species, where trawling attempts to match the fine-scale habitat use of that species. Modularity indicated clustering related to both port and target species in all of the years studied. The formation of new vessel associations (TERGM) was also related to both vessel characteristics. The probability of association varied among the different ports, likely reflecting local differences in fish abundance and distribution. Differences in the formation of associations among targeting categories could reflect differences in fishing tactics in response to the distribution and movements of the species pursued. For example, the Vlissingen vessels are known to specialize on sole in the southern North Sea with chain mats that allow trawling on rough grounds (Rijnsdorp et al. 2008) and formed strongly connected components in our annual networks. The homophily observed within the classifications of both landing port and targeting could result from spatial constraints, choice, or a combination of the two. In contrast with this general pattern, the lack of homophily in the intermediate sole-targeting category suggests that these vessels prefer to form links with others that follow either a high or low sole strategy. Here, the intermediate category could encompass vessels that are attempting to follow one of the other strategies less successfully.

By pursuing the same species from the same home port, vessels will be drawn together in space. Sharing information about recent success could also bring them closer in time. This could occur through either deliberate communication or observation (Allen and McGlade 1986; Gillis and Showell 2002). Such behaviours have been well documented in a wide variety of fisheries, including tuna seiners (Orbach 1977), North Atlantic trawlers (Andersen 1973), Maine lobster boats (Palmer 1990), and Pacific salmon seiners (Orth 1987). The influence of social networks on targeting and catch composition has also been observed among small, open boats in a coastal Jamaican fishery (Alexander et al. 2020). Unfortunately, our annual time scale leaves the relative importance of social influence and environmental constraints unresolved here. Examining such issues would benefit from both a shorter time scale and an independently derived social network that could be compared with spatial and temporal associations at sea. Such comparisons have proven successful in relating social networks online to geographical proximity (Crandall et al. 2010).

Communication networks at sea are most likely related to relationships onshore. Barnes-Mauthe et al. (2015) found that information was shared more freely within ethnic groups in the Hawaiian longline fishery. Both Mueller et al. (2008) and Turner et al. (2014) found that fishers were more likely to share information with others of similar success in a freshwater charter fishery and a marine lobster fishery. Mueller et al. (2008) also found that information was shared exclusively within ports, but preferentially with captains at different marinas, while Turner et al. (2014) assumed a priori that each port formed an independent network in their analysis. In a series of spatially lagged production models, Haskell et al. (2019) established that average revenue per trip in the American Pacific coast groundfish fishery is predicted best by a model that incorporates information sharing while in port rather than at sea. The importance of landing port in network formation seen in our analysis is consistent with communication patterns in other fisheries as well as potentially reflecting geographical constraints.

The motivation for collaboration may vary in pursuit of different species in the same region. Consistent fish distribution and movement patterns devalue information sharing because fish locations can more easily become public knowledge. This was observed when comparing Maine's sea urchin and lobster fisheries (Wilson et al. 2013). Among lobster fishers, collaborative actions and selective information sharing is well documented (Palmer 1990), corresponding to a resource that is biologically variable in space and time. In contrast, urchin fishers from the same region were highly individualistic when the resource was initially abundant and ubiquitous. Later, when the urchin population was depleted, intense competition among fishers hindered collaboration. In the Dutch trawlers, differences between the behaviour of the target species could also contribute to the differing probabilities of vessel association among the targeting strategies.

Interannual dynamics indicated that in our fishery, the network structure itself was not strongly related to changes in vessel associations. The endogenous effects of degree (GWD) and triad closure (GWESP) did not improve the TERGM model as much as the vessel's characteristics — both directly and through homophily. This suggests that influence among peers did not play a major factor in forming associations on the water, which has also been suggested in other social network settings (Lewis et al. 2012). Without dyadic dependence our model would reduce to a simpler generalized linear model (in this case, a logistic regression) without many of the estimation challenges of network models. We could have reached similar conclusions about the effects of all of the other covariates. However, given the prevalence of endogenous effects in the social network literature (Rivera et al. 2010), this should not be done a priori. Their explicit consideration strengthens our conclusions, but may not always be required to make valid inferences.

Alternate methods of modeling network dynamics may provide different insights. Stochastic actor-oriented models (Snijders 2017) have been popular in social network analysis for many years. These models focus on the formation and dissolution of edges (ties, links) originating with specific actors (vertices, nodes). In contrast, ERGMs and their derivatives focus on the prediction of edges existing

Table 8. Temporal exponential random graph model (TERGM) of the probability (expressed as log-odds) of a vessel forming an association (edge) with another vessel as the network advances one time step (1 year) in a longitudinal series (a wave).

Predictor	Estimate	SE	p
Endogenous			
Edges	−7.2884	0.014	<0.001
Temporal stability	1.0425	0.056	<0.001
GWD (α = 1)	2.5872	0.005	<0.001
GWESP (α = 1)	1.1854	0.033	<0.001
Exogenous			
No. of observations	0.0003	<0.001	<0.001
Performance			
Value	3.4889	0.016	<0.001
Homophily (as heterophily)	−3.0985	0.020	<0.001
Targeting (catch composition)			
Value (ref. high sole)			
Low sole	0.1039	0.034	0.002
Medium sole	0.7321	0.036	<0.001
Homophily			
High sole	1.2094	0.019	<0.001
Low sole	1.0136	0.015	<0.001
Medium sole	−0.4419	0.018	<0.001
Landing port			
Factor (ref. Eemshaven)			
Harlingen	−0.5339	0.023	<0.001
Den Helder	−0.5684	0.038	<0.001
IJmuiden	−0.4734	0.030	<0.001
Stellendam	−0.2874	0.020	<0.001
Vlissingen	−0.2385	0.009	<0.001
Other ports	0.2112	0.010	<0.001
Homophily			
Eemshaven	1.2398	0.010	<0.001
Harlingen	1.9921	0.013	<0.001
Den Helder	1.2521	0.019	<0.001
IJmuiden	0.9019	0.015	<0.001
Stellendam	0.7350	0.010	<0.001
Vlissingen	1.1590	0.020	<0.001
Other ports	0.2267	0.009	<0.001

Note: This probability of a function of exogenous (network independent) factors, endogenous factors (network structure), and stability in associations (or their absence — memory) between waves. The edge coefficient is a constant (no covariate). GWD is the coefficient for the geometrically weighted degree distribution, GWESP is the coefficient for the geometrically weighted edgewise shared partner distribution. Both GWD and GWESP have a decay coefficient (α) of 1. The relationship of edge formation to vessel performance is examined in terms of performance value and homophily (the tendency for vessels with similar performances to associate). The latter is represented by heterophily, calculated as the absolute difference between vessel performances. The influence of targeting (proportion of sole in annual catch) and landing port are examined both as simple factors (examining differences among categories) and as homophily coefficients examining preferential associations among similar vessels.

between two vertices. The coefficients generated are rates of edge formation rather than probabilities and thus are not sensitive to the time interval between successive network samples (waves). There has been much recent discussion about the best choice of methodologies (Desmarais and Cranmer 2012; Block et al. 2019), but without a definitive resolution. The choice can be made based on the goal of the study (focus on edges or individuals) or the desire to explicitly represent individual actions. In practice, the fit of the model is usually the final arbiter choice for specific data sets (Leifeld and Cranmer 2019; Desmarais and Cranmer 2012), though some authors feel that statistical and theoretical considerations should be paramount (Block et al. 2019). In addition to the TERGMs that we examined, ERGM methods for dynamic models also include separable exponential random graph models (STERGM; Krivitsky and Handcock 2014). These split the dynamic process between waves into two models: edge formation and edge dissolution. We preferred the TERGM approach to explicitly represent network stability in a single parameter for ease of interpretation, though this excluded the use of AIC with the current software available. Our central goal was not to choose among model methodologies. We were not directly concerned with "microlevel mechanisms" that gave rise to the changes observed in the networks between years (Block et al. 2019). Instead, we primarily wished to account for known covariates, including network structure, in the comparison of vessel performance to network dynamics. Other suggested criteria (Block et al. 2019) that would favour a TERGM approach are that vessels could possibly associate with several other vessels simultaneously and that the focus of our question was better represented by the network edges (vessel associations) than the actions of specific vessels. Ultimately, we chose the TERGM methodology to focus on a single model of change that directly represented the stability of networks edges across time in addition to the other covariates examined.

Employing GAMMs provided a standardization that mitigated the impact of seasonal trends in fish availability on our measure of vessel performance. The smooth components of the GAMMs indicated a decline in trip values in the middle of the years that is consistent across the years examined. This pattern in value landed follows typical landing trends in the main target species (sole and plaice; Poos and Rijnsdorp 2007) and seasonal trends in fishing mortality for both species (Rijnsdorp et al. 2006). In sole, this variation in offshore catch has been attributed to springtime movement into shallow coastal waters to breed and subsequent return to the offshore feeding grounds. Similarly, seasonal variation in offshore plaice catches has been related to southward spawning migrations in autumn followed by a northward return to dispersed feeding grounds.

Our GAMMs predicted catch within a trip rather than catch per unit effort. This allowed effort to be represented in several covariates rather than a single "nominal" effort value. Examining standardized catch also eliminated the statistical concerns associated with an assumed relationship between catch and nominal effort (Aljafary et al. 2019). Effort was incorporated in the model's predictors as days fishing and days at sea without fishing. As expected, more fishing days were related to larger trip landed values. The same was true for days at sea without fishing, similar to earlier results in the Dutch trawl fishery (Rijnsdorp et al. 2000). This is consistent with optimality arguments that postulate more distant fishing opportunities will only be exploited when catches can account for travel costs (Sampson 1991), as predicted by the marginal value theorem from foraging theory (Charnov 1976; Stephens and Krebs 1986). The role of horsepower as a predictor was to account for advantages such as higher speeds, the ability to deploy gear more effectively in tidal currents, or to use heavier gear. However, the utility of this advantage could vary with species and bathymetry. At least one of the horsepower terms was significant in each of the modeled years. When horsepower alone was significant, the catch value per trip increased with horsepower. A positive interaction of horsepower and days fishing suggested that horsepower increased the efficiency of trawling time. When significant, the interaction between horsepower and nonfishing days was negatively related to trip value. This indicated a reduction in trip value with travel for higher horsepower. It is also consistent with marginal value theorem arguments, since greater horsepower is associated with larger, faster vessels that allow the affordable exploitation of less profitable distant areas. Vessels with lower horsepower would be expected to exploit more distant areas only when the expected catch was high. Other covariates such as home port, fishing strategy, and vessel network metrics were not included as fixed effects in the standardization so that they could be examined in the subsequent network analysis.

Using the vessel random effects of the GAMMs as the annual performance measure allowed vessels to be equitably compared. Each random effect is essentially a vessel-specific variation in expected catch that is standardized among all vessels. Vessel effects defined this way incorporate all vessel differences not explicitly represented in the model's covariates. In our standardization, it removed the effects of vessels' physical characteristics as well as seasonal influences on catch where vessels fished more at different times of the year.

Our study highlights a number of directions for future research in networks among fish harvesters. The deeper exploration of causality discussed earlier suggests additional analysis with different models, shorter time steps between waves, or both. Shorter intervals (months or weeks) would be more sensitive to possible causal relationships in the fleet on a scale more comparable to a single trip. Examining the relationship between social networks on shore and the association networks on the water would require additional data. In the Dutch beam trawl fleet, the home ports and the landing ports are similar, providing poor contrast to investigate the relationship between the two networks. However, the traditional fishing port of Urk does not act as a landing port. Instead, its vessels fish from a number of other coastal Dutch ports. The more traditional construction of social networks based on surveys within Urk would allow the comparison of associations within the community with landing port use and vessel association at sea. Additionally, the recent introduction of electric pulse fishing (van Marlen et al. 2014) provides a unique opportunity to study the spread of innovation through the fleet. This may reveal the role of weak ties in the fishery more effectively than our association network.

The relationship between vessel performance and vessel networks could also be incorporated into catch standardizations. Given the relatively small effect of covariates related to degree and closure in our TERGM, we may be tempted to ignore them and use generalized linear mixed models or GAMMs as has been done in the past (Maunder and Punt 2004). However, given the ability to construct association networks from vessels at sea, network metrics could be easily included in these models, as was done in Barnes et al. (2017). Where possible, and especially when fleet structure is known to be changing, we recommend examining the underlying changes in vessel interactions through network-based covariates in catch standardizations.

The methodology of this paper provides a framework to examine novel questions about vessel association and success in other fisheries. Our standardization of performance using GAMMs mitigates the effect of temporal variation in landed value that is the result of seasonal fluctuations in fish availability in subsequent analyses. The TERGMs incorporate both typical fishery covariates and endogenous network characteristics, providing hypothesis tests that more accurately represent the precision of the coefficients. We have established that vessel performance is related to network dynamics, but this is just the first step towards a richer investigation of effort dynamics in the North Sea.

Acknowledgements

This work was supported by a Natural Sciences and Engineering Research Council of Canada Discovery Grant to D.M. Gillis. We are grateful for the data collection and ongoing stewardship by the researchers and staff of Wageningen Marine Research (Haringkade 1, 1976 CP IJmuiden) and the former IMARES, without which this work would not be possible. We also thank Philip Leifeld (University of Essex, UK) for taking the time to answer questions regarding his btergm package. Finally, we appreciate the comments of the reviewers, especially the encouragement to explore social network theory in greater depth that resulted in a richer and broader paper.

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Appendix A

These appendix figures provide a more detailed breakdown of the VMS locations illustrated in Fig. 1. They illustrate the different locations exploited from each port and the similar spatial exploitation among the years studied.

Fig. A1. The VMS estimated location of trawls from each of the landing ports studied for all years.

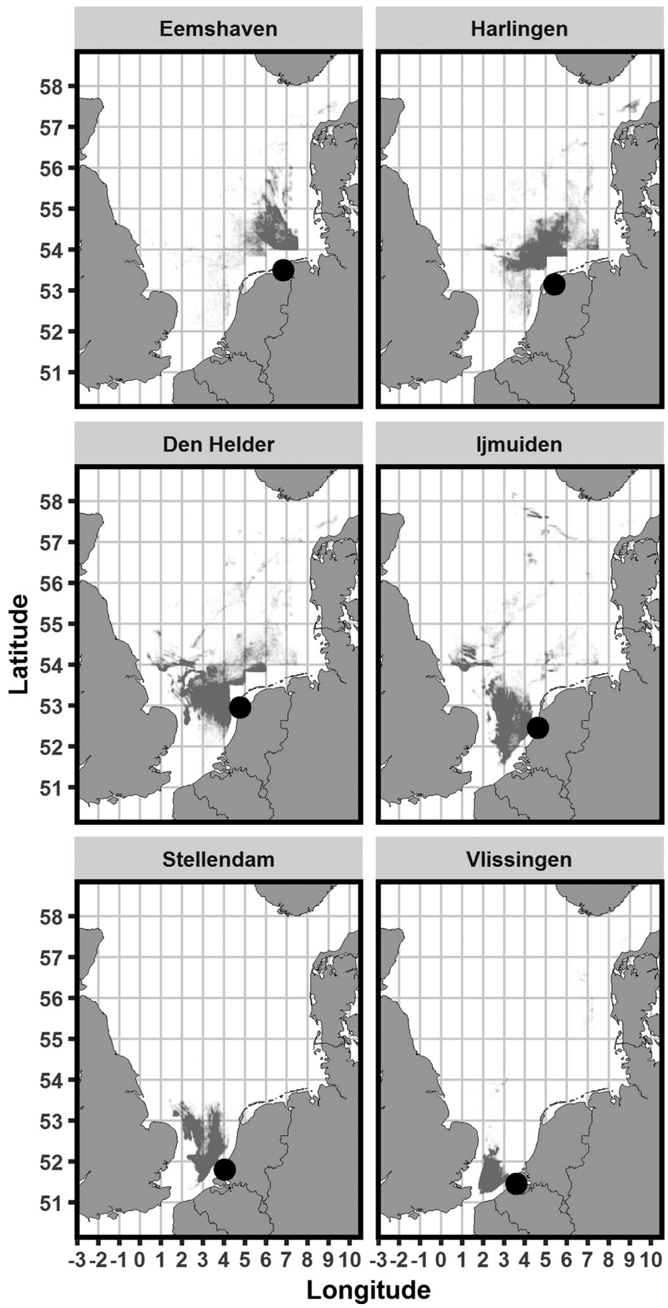

Fig. A2. The VMS estimated location of trawls from all landing ports examined for each of the years studied.