

Title page: Global trade network patterns are coupled to fisheries sustainability

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This PDF file includes:

Main text

Table 1

Figures 1-3

Supplementary Information

1 **Global trade network patterns are coupled to** 2 **fisheries sustainability**

3 **Abstract**

4 Seafood trade is increasingly globally connected and short-lived. The rapid evolution of
5 seafood trade networks alongside the decline in biomass of many marine populations
6 raises important questions about the role of global trade in fisheries sustainability.
7 Mounting empirical and theoretical evidence shows the importance of trade network
8 development to natural resource outcomes. However, characteristics associated with
9 connectivity and duration of trade networks are rarely used to understand fisheries
10 sustainability. In a global analysis of over 400,000 bilateral trade flows and stock status
11 estimates for 746 fish and marine invertebrate stocks from 222 countries, we reveal
12 patterns between seafood trade network characteristics and fisheries sustainability. A
13 dynamic panel regression analysis shows that more clustering and fewer trade
14 connections within networks were associated with higher biomass in fishery stocks. From
15 1995 to 2015, we found that these indicators developed unfavorably for fisheries
16 sustainability with increased numbers of trade connections and decreased clustering.
17 Unlike previous studies, we found no relationship between the duration of trade
18 connections and network modularity with fisheries sustainability. Our results highlight the
19 need to monitor trade networks in conjunction with fished populations and the opportunity
20 to foster more sustainable fisheries through improved coordination and partnerships
21 between fisheries authorities and trade organizations.

22

Keywords: marine fisheries; seafood trade; network characteristics; resilience; serial exploitation; stock status

Significance statement

Can regulating local fisheries alone achieve fisheries sustainability? In an analysis of over 400,000 bilateral trade flows and stock status estimates for 746 fish and marine invertebrate stocks from 222 countries we found that high connectivity - including high numbers of trade connections and low levels of clustering - is coupled to low fishery stock status. These results highlight the value of regulating and monitoring trade networks along with fisheries. Thus, coordination and partnerships between international and national trade organizations and fisheries authorities presents a powerful new pathway for fostering sustainable fisheries.

1. Introduction

Seafood trade has become globally connected and short-lived (1). In 2018, global seafood trade facilitated the exchange of more than 40 million metric tons of seafood, approximately 38% of global seafood production (2). Today, the trade of seafood is primarily characterized by short-lived trade connections lasting only a single year (3) and a high level of connectivity between trading countries; approximately 65% more trade partners for each country than in the early 1990s (1). Growth in the seafood sector has been accompanied by a doubling of *per capita* seafood consumption since the 1960s (2). This growth is expected to continue given the increasing reliance on seafood as a source of income, food, and nutrition (4). The resource base required to support this growing demand is, however, in many cases dwindling. Many marine and other fisheries have become increasingly overfished in recent years (5), threatening fishery livelihoods and global food security (6).

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48 Trade network patterns impact the sustainability of fish and invertebrate populations and
49 vice versa. In many cases, fisheries have experienced rapid serial exploitation. An
50 overexploited stock of one species is substituted by another stock from within the trade
51 network at an accelerating pace (7–9). Theoretically, the export of seafood can lead to
52 overfishing or collapse in unregulated, open-access fisheries (10, 11) if the cost of
53 exploitation is lower than the prices gained through trade (12–14). This relationship is
54 affected by subsidisation (15). However, if fisheries are effectively regulated based on
55 estimates of sustainable exploitation, increasing prices are not expected to lead to
56 overexploitation (16, 17).

57

58 We hypothesize that the connectivity of a seafood trade network can impact the
59 sustainability of fished and traded marine populations. In highly connected trade networks,
60 new stocks with higher biomass can substitute overfished stocks (12). In this way,
61 exploitation can spread by serial substitution of stocks (18, 19). Furthermore, high
62 substitutability allows multiple markets to drive up prices which increases the incentive to
63 exploit stocks past their sustainable limits (20). On the other hand, if a trade network is
64 small and poorly connected, the impact of supply shifts is likely to be contained amongst
65 a smaller number of trade partners (21, 22). Theoretically, such a network could have less
66 potential for adverse effects on a species' global stock status (23).

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68 We also hypothesize that the duration of trade connections can impact the sustainability
69 of fished and traded marine populations. Global empirical studies illustrated that the trade
70 in marine invertebrates developed five to six times faster in 1990 than in 1960, driving the
71 serial overfishing of populations globally (24). These studies argue that short-lived trade
72 connections may be incongruent with the time frames that fisheries assessments and

management require to be effective, for instance, in the U.S., stock assessments are conducted every two to five years (25). In this way, trade-driven fishing pressure and overfishing may go unnoticed by fisheries managers, even in effectively regulated fisheries (26). Thus, short-lived trade connections could adversely affect species' stock status.

Here, we tested the hypotheses that highly connected trade networks and networks characterized by short-term trade connections between countries are correlated to globally lower sustainability of marine fish and invertebrate populations (henceforth: fishery stock status) on a dataset containing over 400,000 bilateral seafood trade flows between 1995 and 2015 (27) and stock status estimates for 746 marine fish and invertebrate stocks from 222 countries (28). We evaluated our hypothesis on highly connected trade networks using commonly used network connectivity indicators (29, 30): *modularity* measures subsystems of countries that exhibit stronger internal connectivity, *clustering* describes cliquishness in networks, and *degree* represents the number of trade connections (SI Appendix Table S5). We evaluated our hypothesis on *trade duration* by categorizing bilateral trade connections as short-term (0-4 years) or long-term (>4years). We tested the relationships between fishery stock status and trade network characteristics using dynamic panel regressions. Note that the causal relationships between the stock status and their respective trade networks may be bidirectional: fishery stock status may impact the trade network that relies on it and, in turn, the trade network may impact the status of the stock upon which it relies. We accounted for potential reverse causality by using dynamic panel regressions with instrument variables to only measure the impact of seafood trade networks on fisheries sustainability.

2. Results

2.1. Evolution of stock status and network characteristics over time

We evaluated stock status as the ratio of stock biomass (B) to the biomass when fished at maximum sustainable yield (B_{MSY}), a common management target (31). We used an ensemble model (32) to estimate time series of stock status from FAO landings data (28). A B/B_{MSY} ratio of 1.0 indicates a fully exploited stock, ratios less than 1.0 indicate an overexploited fishery. From 1995-2015, we estimated that, on average, the evaluated species groups have been overexploited ($B/B_{MSY} < 1.0$) and that their stock status has declined (Figure 1).

Modularity, which measures the strength of internal connectivity among subsystems of network nodes, ranges from zero to one where a value of one describes a network that consists of highly interconnected subsystems of countries with few connections between the subsystems and a value of zero describes networks in which countries are equally connected amongst one another. The *modularity* values across the species groups' trade networks were low but increasing. Average values ranged between 0.019 in 2000 and 0.035 in 1999. In comparison, the global food trade network modularity ranged between 0.065-0.095 (33).

Clustering, which refers to cliquishness in networks, measures the number of triangular connection relative to all possible triangular relations. Triangular connections form, if country X trades with country Y and country Z, while country Y also trades with country Z. Clustering values range from zero to one where a value of zero indicates few triangular connections and a value of one indicates that all countries are connected amongst one another. We observed relatively low *clustering* values that decreased slightly between 1995 and 2015. In the last year, there were 16% fewer triangular relations compared to

the first year. The observed maximum value of average *clustering* was for 1998 (0.29) and decreased to its lowest value in 2011 (0.25).

Degree represents the average number of trade connections per country with larger numbers indicating more highly connected trade networks. The average degree of species group trade networks increased over the observed period. Degree peaked at a value of 14.6 of trade connections in 2014, which means that each country had more than 14 trade partners on average per species group from 221 possible trade partners. Overall, the average number of trade partners increased by 22.9% from 1995 to 2015. This observation reflects the fact that the number of trade connections in the entire international seafood trade network has increased in recent decades (1).

We measured *trade duration* as the percentage of trade connections lasting longer than four years. Values of *trade duration* range from 0 to 1 with zero indicating that no trade connections lasted longer than 4 years and 1 indicating that all trade connections lasted longer than four years. The value of four years represents the median duration of trade connections in our data. Trade duration increased over time and peaked at a value of 0.55 in 2015. In our sample, *trade duration* across all species groups increased by 13.9% between 1995 and 2015. Despite the high number of single-year trade connections reported in (1) for the entire seafood trade network, our data showed that the proportion of long-term trade connections across all species groups and exporters increased over time.

2.2. Impact of Network Characteristics on Stock Status

We used dynamic panel regressions to assess the impact of trade network characteristics on the status of fishery stocks globally. For our assessment, we matched UN Comtrade

reported seafood trade flows (27) to stock status estimated from FAO reported landings (28). The data contained 27 broader taxonomic species groups which include taxa such as crab, mackerel, and sole (SI Appendix Table S6). We used dynamic panel regressions, in particular, Generalized Method of Moments (GMM) estimations with lagged dependent variables as covariates and lagged covariates as instruments to eliminate potential reverse causality. We evaluated two specifications of the dynamic panel regressions. Model 1 (Table 1) used detailed information by evaluating the continuous B/B_{MSY} estimates as regressand. Model 2 (Table 1) tested whether stock status was categorized as overfished ($B < 0.75 B_{MSY}$) or not. Low stock status levels are more accurately estimated with the ensemble model than high stock status, therefore, Model 2 reduced potential inaccurate input.

We report two additional GMM estimations without lagged dependent variables and year dummies (SI Appendix Table S7) to contrast our results with model estimates that may contain reverse causality. In addition, we tested the same model for three different sets of species groups depending on their contribution to global aquaculture (SI Appendix Table S8 & S9).

Model 1 and Model 2 results indicated that higher levels of *clustering* were associated with higher stock biomass levels (Table 1). *Clustering* was positively associated with continuous B/B_{MSY} in Model 1 ($p=0.018$) and had a significantly negative coefficient in Model 2 ($p=0.019$). In addition, *clustering* remained statistically significant when using different sets of species groups and excluding lagged dependent variables but not when including year dummies (SI Appendix Table S7 & S9); the latter might indicate that there were not sufficient variations around time trends.

A higher number of trade connections was indicative of overfished stock status (Table 1). *Degree* was not statistically significant in Model 1 ($p=0.430$) but was positively correlated with the dependent variable in Model 2 ($p=0.001$) indicating that countries with more trade connections had a higher proportion of overfished stocks. In addition, *degree* remained statistically significant when excluding lagged dependent variables but not when including year dummies or using different sets of species groups (SI Appendix Table S7 & S9).

In contrast to our hypothesis that trade networks with low *modularity* would be associated with low stock status, we found that *modularity* was not significantly associated with stock status in any of the six tested model specifications.

Similarly, in contrast to our hypothesis that trade networks with low *trade duration* would be associated with low stock status, we found that *trade duration* was not significantly associated with stock status in any of the six tested model specifications.

2.3. Trade network evolution and stock status of species groups

The more general associations found between network characteristics and stock status patterns in the GMM estimations held for all selected species group networks, yet, each species group showed distinct characteristics. This section illustrates the characteristics observed in species groups with the maximum and minimum values of the significant indicators ($p<0.05$; *clustering* and *degree*) in the GMM estimations (Table 1). Rock lobster and haddock exhibited the lowest and highest clustering values and sea bass and crab the lowest and highest degree (Figure 2).

Rock lobster had a lower clustering value than haddock and the average stock status of rock lobster was consistently above that of the haddock network (Figure 3B). From the GMM estimator results, we would expect the opposite: that the stock status of rock lobster would be below that of the haddock network. The maximum *clustering* value of all species groups was observed for rock lobster in 2009 which corresponded to an average stock status of 0.85 B/B_{MSY} (Figure 2A). The minimum *clustering* value of all species groups was seen for haddock in 1996 which corresponded to an average stock status of 0.66 B/B_{MSY} (Figure 2B). The *clustering* values of the rock lobster and haddock networks over time developed in opposite directions: *clustering* of the rock lobster network increased but *clustering* of the haddock network decreased (Figure 3A). The *clustering* value of the rock lobster network increased from 0.16 in 1998 to 0.22 in 2015, whilst *clustering* in the haddock network decreased from 0.45 in 1998 to 0.37 in 2015. At the same time, the stock status of both decreased during the observed time period. The average stock status of haddock peaked in 2009 at a value of 0.73 B/B_{MSY} , and by 2015 had declined to levels below 0.6 B/B_{MSY} . The stock status of rock lobster was always above an overfished stock status ($>0.75 B/B_{MSY}$) but declined between 1995 (0.95 B/B_{MSY}) and 2015 (0.82 B/B_{MSY}).

Degree almost doubled for the crab network whilst *degree* stayed stable at a low value for the sea bass network (Figure 3C). The average stock status of crab and sea bass decreased over time. The stock status of crab decreased from 1.06 B/B_{MSY} in 1998 to 0.88 B/B_{MSY} in 2015 and the stock status of sea bass decreased from 1.00 B/B_{MSY} in 1998 to 0.78 B/B_{MSY} in 2015. Average sea bass stock status declined by 22.1% and crab by 20.5% from their initial level in 1995. From the GMM estimator, we would expect the stock status of crab to be lower which was only the case in the last couple of years (2010-2014; Figure 3D). In 2015, the *degree* of the crab network was at its highest value (20 trade connections) and that of the sea bass network was at its lowest value (3 trade

connections). The high *degree* of the crab network was reflected in a dispersed network with many trading partners and many connections (Figure 2C). Similarly, the low *degree* of the sea bass network was reflected in the few (but high-volume) trade connections (Figure 2D).

3. Discussion

Our results reveal global relationships between trade network structure and marine fisheries sustainability. Fishing to feed an increasing human population exerts huge pressure on fisheries worldwide (2, 34) and much of this demand has been supplied by the development of the global seafood trade network (1). In line with our hypothesis, we found that connectivity - including high numbers of trade connections (*degree*) and low levels of *clustering* - is coupled to low fishery stock status. Short-term trade connections (*trade duration*) and low *modularity* were not correlated to low stock status.

Multiple mechanisms could explain the relationship we found between clustering and degree with fisheries sustainability. First, trade volumes can be substituted between closer trade partners before one stock is overexploited. Thus, individual stocks would not have to reach overexploited states because other options through trade exist. Such substitution has been shown to occur between well-managed stocks (35). Second, network theory posits that high connectivity facilitates the spread of supply shocks (22, 36). For instance, shocks driven by declines in biomass or increases in demand create new demand across a network (21, 37). This means if a supply shock occurs in a seafood trade network fewer trade connections and higher clustering would contain the spread of such a shock in a smaller set of countries. Overall, we found that clustering decreased and degree increased

between 1995 and 2015. Continuing these trends in the future may negatively impact the sustainability of fisheries through mechanisms such as substitutability and supply shocks.

The lack of empirical support (in our study) for associations between stock status and network modularity contrasts with earlier studies (33, 36). Modularity was not identified as a significant determinant of fisheries sustainability in any of our models. Generally, modular networks are thought to diminish the propagation of supply shocks (22, 36). However, this relationship is conditional on network structure (33). Modularity increased the sustainability of natural resources only if importers and exporters had highly unequal numbers of trade partners. This could explain why we did not detect a relationship, since importers and exporters in our dataset had trade connections that were slightly positively correlated.

Our analysis highlights the need for a critical examination of the mechanisms that determine seafood trade network structure and its relationship to fisheries sustainability. We found that between 1995 and 2015, the number of trade connections across species group trade networks increased. In large part this may be due to increased trade liberalization (38–40). At the same time, new trade connections were not formed between countries that already shared trade partners because the clustering in networks decreased. International trade bodies that promote trade liberalization could therefore consider the role that trade agreements and policies have in determining trade network structure. In parallel, such investigation needs to consider the impacts of trade on livelihoods and the opportunity costs associated with not opening new trade routes or closing existing ones (41, 42). In addition, our results suggest that agreements which promote the development of highly connected trade networks are not likely to benefit fisheries sustainability. Future research should further examine the mechanisms by which

changes in trade network patterns affect fisheries sustainability. This could be undertaken with higher resolution analysis such as cross-case study comparison to help differentiate trade impacts under different local policies and institutional settings (42).

Importers and exporters are recently experimenting with new types of trade relationships that could support the development of clustering in trade networks. Aligning incentives between importers and exporters might be achieved if maintaining food supply and maintaining fisheries sustainability are co-dependent. Singapore, for example, has no autonomous food security and therefore has trade contracts that guarantee supply with a few supplying countries (43). Exploring under which conditions such trade contracts support fisheries sustainability could guide future trade policy development. Another strategy is that importers enhance trade relationships through mutual collaboration. For instance, the European Union recently appointed a Chief Trade Enforcement Officer to help strengthen transparency and sustainability policies in seafood exporting countries (44). In addition, seafood certification and import rules may enhance fisheries sustainability. For example, the EU bans seafood imports that have been given a “red card” for inadequately addressing Illegal, Unreported, and Unregulated Fisheries (45, 46).

Avenues of research departing from our analysis include improving stock status assessments and including domestic trade in such analyses. Although the ensemble model developed here performs better than alternative data-poor stock assessment models, its estimates of stock status remain less accurate than sophisticated age-structured assessment models with larger data-requirements (47). While an increasing proportion of seafood is traded globally (FAO, 2020), domestic trade and consumption still account for a large share of seafood demand and associated pressures on marine

ecosystems (48, 49). In cases where seafood is mostly traded domestically, the impact of the international trade network will likely be less apparent.

Globally improving the quality of seafood trade data will help facilitate new insights into the relationship between trade and sustainable fisheries. Traded commodities are often mislabeled and data is collected in commodity codes rather than by individual species (50, 51). This impedes resolved analyses of trade and fisheries data (Watson et al., 2015) because many commodity codes cannot be linked to specific species (e.g., processed “whitefish”) and aquaculture grown species are traded in the same commodity codes as wild capture species (28, 52, 53). Thus, the collection of trade data would ideally be at species resolution and differentiate between aquaculture and wild capture (54).

To achieve more sustainable fisheries globally, fisheries and ocean management cannot focus on regulating local fisheries alone. To date, the primary approach used to prevent unsustainable exploitation is through the management of fisheries using measures such as quota allocation systems and spatial management measures (55). Such measures have had varying degrees of success to date (17, 56). Controlling the trade of seafood provides a second promising avenue to prevent conditions for unsustainable exploitation. This network approach poses the challenge for fisheries authorities and trade bodies to collaboratively investigate the effect of international and bilateral trade policies such as trade liberalization, multilateral agreements, and trade contracts on the structure of seafood trade networks and the sustainability of the fisheries on which they depend. This also entails collecting and monitoring trade network data in parallel with catch and stock status data. This agenda represents a substantial departure from current policies for fisheries sustainability that focus on fisheries in isolation. It highlights the need for

coordinating and forging partnerships between and amongst national and international trade institutions to drive global fisheries sustainability.

4. Methods

4.1. Global seafood trade data, stock status estimates, and data matching

We used trade data from a processed version of the UN Comtrade International Trade Statistics Database (27) called BACI (57, 58) and we estimated stock status from the FAO Fisheries Landings Database (28). The dataset we constructed from these contains 401,027 bilateral trade transactions between 222 countries and 746 fish and marine invertebrate stocks classified into 27 distinct species groups from 1995 to 2015. The data consists of time series of (i) bilateral trade flows between import and export countries; (ii) the mean stock status of individual stocks contributing to each species group; and (iii) network characteristics of connectivity and duration of the trade networks for each species group.

To construct this dataset, we first downloaded the FAO reported annual, country-level catch time series of individual fish and marine invertebrate stocks (28). From this data we constructed a time series of stock status or B/B_{MSY} using an ensemble model of four individual catch-only stock assessment models (SI Appendix S1.1; SI Appendix Table S1) and two spectral properties of the catch time series (32, 47). B/B_{MSY} refers to biomass (B) that would sustain maximum sustainable yield (B_{MSY}). We included B/B_{MSY} and one categorical indicator to represent overfished ($B < 0.75B_{MSY}$) stock status. We chose to use

catch-only stock assessment estimates because stock assessment data are not available for many countries (e.g., (56)).

Second, we constructed trade networks from the BACI data which provides self-reported, annual, bilateral flows of 65 seafood commodity codes from UN Comtrade International Trade Statistics (SI Appendix S1.2). These groups correspond to the Harmonized System (HS) codes from 1992 (World Customs Organization, 2020). From this database, we constructed global seafood trade networks for 27 species groups from 65 seafood HS codes (SI Appendix Table S6) following best practices identified by (1).

Finally, we had to match the data because stock status estimates use individual species whereas the 1992 seafood HS codes in the UN Comtrade data vary in their taxonomic resolution (SI Appendix 1.3). The commodity code descriptions contain common and scientific names of species, genus, family, order, class, and phylum. When a commodity code was not specified at the species level, we chose the next level of taxonomic resolution to match them to species level stock status estimates. When commodity code descriptions were at a higher taxonomic resolution than class (e.g., 'Fish livers and roes, frozen'), we excluded the stock from the dataset. Thus, stock status estimates of multiple species (on avg. 1.5 species per stock status estimate) were associated with individual trade flows.

4.2. Network characteristics

We computed commonly used network connectivity indicators (29, 30): *modularity*, *clustering*, and *degree*; and a categorical variable for *trade duration* (SI Appendix Table

S5). All indicators were computed at the network level, which means that there is one value for each indicator per year and species group.

Modularity captures the presence of subsystems of countries that exhibit stronger internal connectivity (59). A more modular network contains many subsystems of countries that exhibit stronger internal connectivity (60). Values for *modularity* range between zero and one. *Modularity* values closer to one indicate many highly connected subsystems in the network.

Clustering measures connectivity as the ratio of adjacent triangular connections between countries (cliques of countries) in a network compared to all possible triangular connections (61). Adjacent triangular connections form, if country X trades with country Y and country Z, while country Y also trades with country Z. Values for *clustering* range between zero and one. *Clustering* values closer to one indicate many cliques in the network. Cliques are delineated regardless of their links' directionality, i.e., whether links are export or import links. We calculated *clustering* using the *igraph* R package (62). Social networks tend to be characterised by higher levels of clustering (e.g. >0.15) than randomly formed networks (30).

Degree is a measure of the average number of trade connections per country (63, 64). In a highly connected network, the average *degree* will be high. The number of trade partners is calculated regardless of the directionality of a link. For example, if a country exports a commodity to two countries and imports a commodity from three countries, its node *degree* is five.

Trade duration is defined as the percentage of trade connections lasting longer than four years. *Trade duration* is an essential indicator in trade economics and often measured in years (65, 66). Our hypothesis on *trade duration* differentiates between short- and long-term trade connections. Therefore, we chose to compute a categorical variable taking the median value of four years as the cut-off value. We could only compute the trade duration variable from 1998 because we had no data available from before 1995 to accurately assess how long countries have been trading. If a trade connection has existed for four years or more, the categorical variable is one; if less than four years, the categorical variable is zero. For example, for a trade connection lasting from 1995-1999, the years 1998 and 1999 would be indicated with 1, and the years 1995-1997 would be indicated with 0. We used the average value of *trade duration* at the network level. *Trade duration* values closer to one can be interpreted as long-term and closer to zero as short-term.

4.3. Dynamic panel regression analysis

We tested the hypotheses that highly connected trade networks and networks characterized by short-term trade connections between countries are correlated to globally lower fishery stock status. We tested the relationships between fishery stock status and trade network characteristics using dynamic panel regressions. We needed to control for potential reverse causality: (1) that stock status affects network characteristics, (2) that network characteristics affect stock status, or (3) the combination of the two. The estimated coefficients using ordinary least squares or fixed effects estimators would reflect all three directions. The way to address this problem is to identify instrument variables that affect network properties and are not directly correlated with stock status. Therefore, we used a dynamic GMM estimator with 2- to 5-year lags of the covariates to assess the contemporaneous correlation between network patterns and stock status. The characteristics used for the estimations of trade network connectivity were based on the

year 1995 except for trade duration for which our observations encompass values from 1998 onwards. Therefore, the estimations include all years after 1998. The parameters of the GMM estimations are interpreted as follows: suppose the estimated coefficient of covariate one is beta, then if covariate one increases by one unit, ceteris paribus, the response variable is expected to increase beta units. We evaluated model significance using the p-value with a ≤ 0.05 alpha value.

We ascertained the validity and robustness of our results using a number of approaches (SI Appendix S2). We tested for autocorrelation of the first-differenced error term using the Arellano-Bond test for AR(2) and overidentification of instruments using the Hansen test (67, 68). P-values for the AR(2) test and the Hansen test are larger than 0.10 indicate that the first-differenced error term is not autocorrelated of order 2 and that the assumption of instrument exogeneity is not violated. In addition, we assessed the robustness of our results by providing GMM estimations including three different sets of species groups in the analysis based on their contribution to global aquaculture (SI Appendix Table S8). Finally, we provided additional GMM estimations without lags of the covariates and with year dummies to contrast our results with those that may contain reverse causality (SI Appendix Table S7).

Model specification

We employed three model settings for the GMM estimator. All are dynamic GMM estimators in which the network effects on fishery stocks were assumed to be contemporaneous. We used 1- and 2-year lags of stock status to lessen dynamic endogeneity. We refer to this specification as the baseline model. It assumes the functional form described in equation 1 (Table 1, Model 1):

438

$$439 \quad \frac{B}{B_{MSY}_{git}} = \lambda + \beta_1 (B/B_{MSY})_{git-1} + \beta_2 (B/B_{MSY})_{git-2} + \beta_3 clustering_{gt} + \beta_4 degree_{gt}$$

$$440 \quad + \beta_5 trade\ duration_{gt-1} + \beta_6 turnover_{git} + \varepsilon_{gt}$$

441

$$442 \quad where \varepsilon_{gt} = u_{ig} + v_{igt} \quad (1)$$

443

444 Where continuous stock status (B/B_{MSY}) of species group g traded by exporter i in year t
 445 is predicted by the 1- and 2-year lags of stock status, the network level characteristics
 446 (*clustering* and *degree*), and trade duration of species group g in year t . The error term is
 447 composed of two terms: first, u_{ig} represents unobserved exporter-species time-invariant
 448 fixed effects. Second, v_{igt} represents a stochastic error term to introduce variation in other
 449 variables that could potentially affect stock status but are not included in our model.

450

451 The second model settings use the same GMM estimator but predicts a binary variable.
 452 We used the B/B_{MSY} estimates and created a dummy variable that we define as overfished
 453 ($B/B_{MSY} < 0.75$) stock status. The dummy variable is 1 for overfished stock status and
 454 otherwise 0. It assumes the functional form described in equation 2 (Table 1, Model 2):

455

$$456 \quad Overfished_{git} = \lambda + \beta_1 (B/B_{MSY})_{git-1} + \beta_2 (B/B_{MSY})_{git-2} + \beta_3 clustering_{gt}$$

$$457 \quad + \beta_4 degree_{gt} + \beta_5 trade\ duration_{gt-1} + \beta_6 turnover_{git} + \varepsilon_{gt}$$

458

$$459 \quad where \varepsilon_{gt} = u_{ig} + v_{igt} \quad (2)$$

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Table 1. GMM estimations with instrument variables using B/B_{MSY} and $B < 0.75 B_{MSY}$ as regressand. Windmeijer's finite-sample corrected standard errors in parentheses. Significance levels reported as * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The p-value AB test for AR(2) and p-value Hansen test indicate that the first-differenced error term is not autocorrelated of order 2 and that the assumption of instrument exogeneity is not violated.

Network Characteristics	Model 1 B/B_{MSY}	Model 2 $0.75 B/B_{MSY}$
Modularity	0.0357 (0.0829)	0.106 (0.130)
Clustering	0.219* (0.0923)	-0.325* (0.138)
Degree	-0.00127 (0.00160)	0.00980*** (0.00286)
Trade duration	0.0142 (0.0245)	-0.0116 (0.0380)
$(B/B_{MSY})_{t-1}$	0.579*** (0.0320)	0.407*** (0.0287)
$(B/B_{MSY})_{t-2}$	0.158*** (0.0202)	-0.0908*** (0.0218)

N	7346	7346
p-value AB test for AR(2)	0.919	0.641
p-value Hansen test	0.428	0.553

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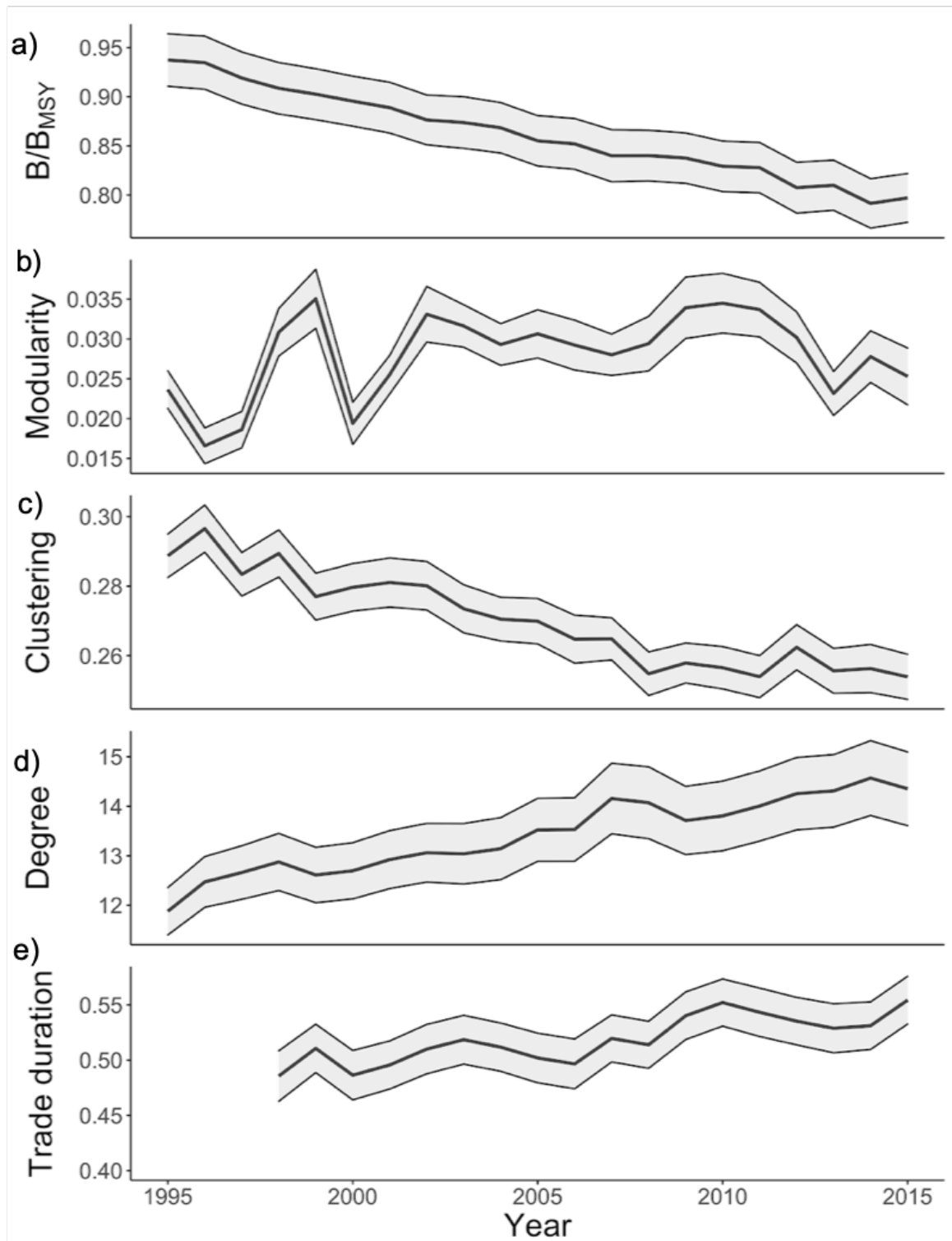


Fig. 1: From top to bottom: mean and 95% confidence intervals for (a) biomass compared to biomass when fished at maximum sustainable yield (B/B_{MSY}), (b) *modularity*, (c) *clustering*, (d) *degree*, and (e) *trade duration*

641 of global seafood trade networks of all species groups between 1995 and 2015. The *trade duration* time series
642 begins in 1998 because its calculation depends on the data availability four years previous.

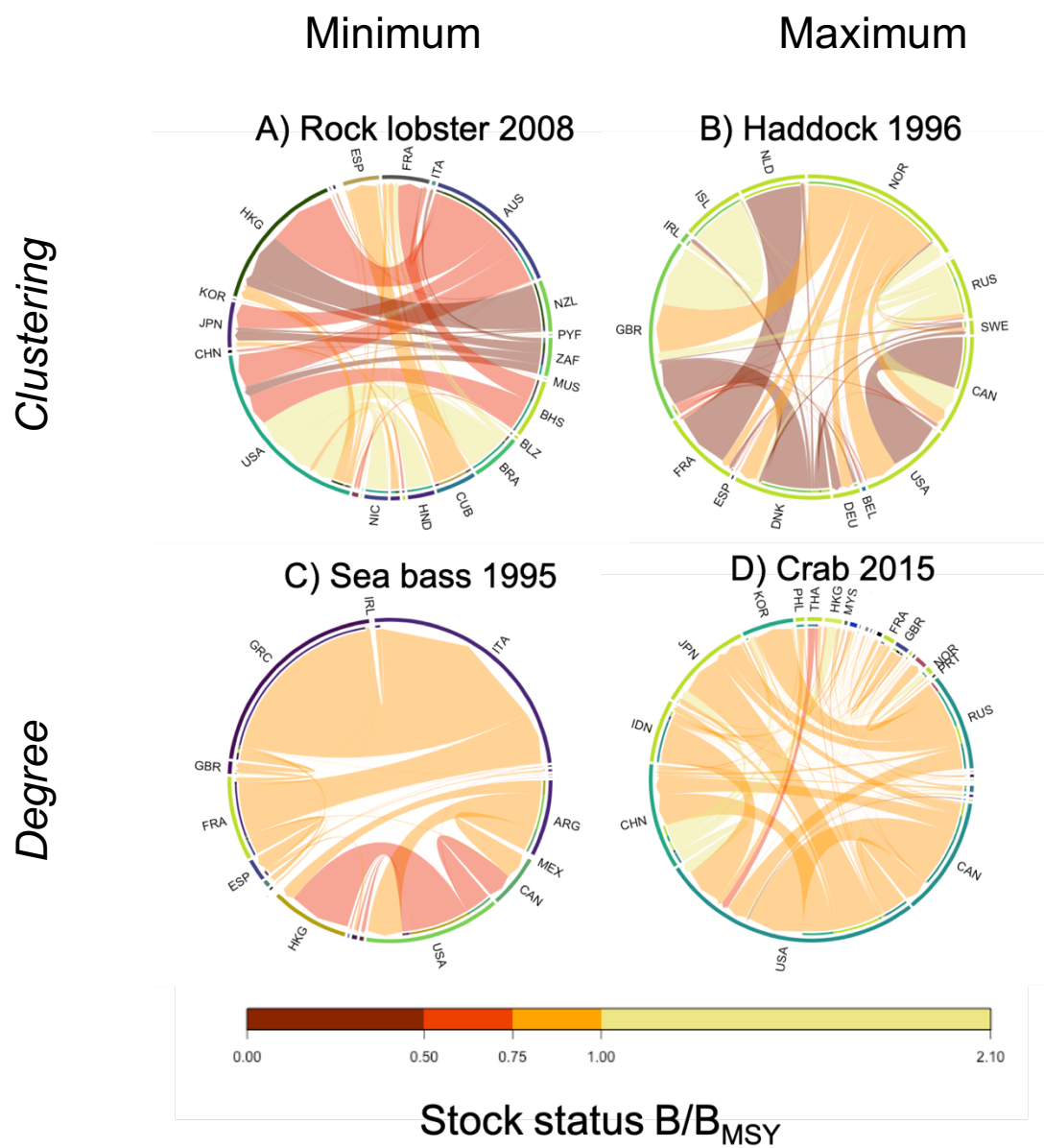


Fig. 2: The trade network figures illustrate the species and years corresponding to the minimum (left) and maximum value (right) of *clustering* and *degree* (excluding the *modularity* and *trade duration* as these indicators were not significant). Arrow color indicates stock status where yellow is associated with high stock status ($B/B_{MSY} > 1$) and dark red is associated with low stock status ($B/B_{MSY} \leq 0.5$). Arrows indicate the direction of trade and the weight of the arrows indicates annual traded volume for a given importer-exporter pair.

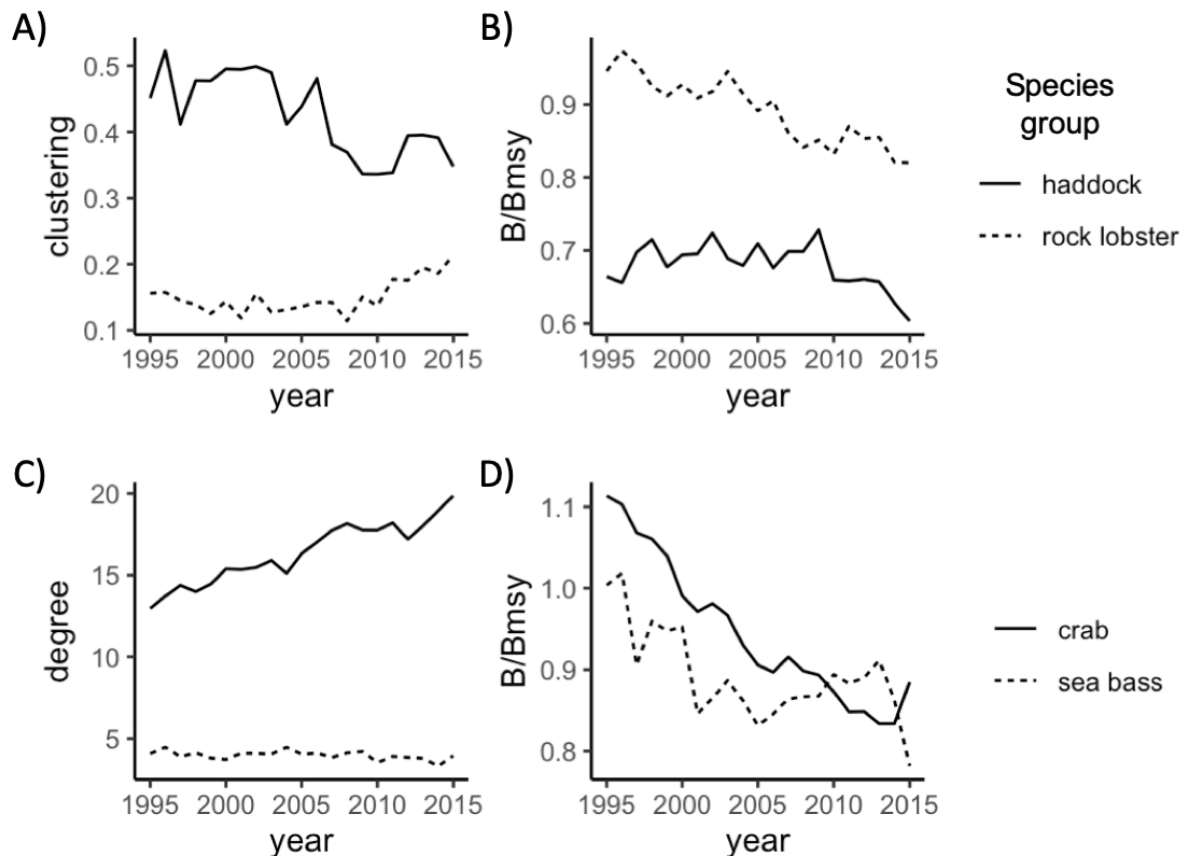


Fig. 3. Time series of network characteristics and stock status of species groups corresponding to the minimum and maximum value of *clustering* and *degree*. The panels show A) *clustering*, and B) B/B_{MSY} for haddock and rock lobster, and C) *degree*, and D) B/B_{MSY} for crab and sea bass.

Supplementary Information for

Global trade network patterns are coupled to fisheries sustainability

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This PDF file includes:

Supplementary text

Figures S1 to S4

Tables S1 to S9

SI References

Supplementary Information Text

S1. Datasets and matching

S1.1 FAO stock status estimates

S1.1.1 FAO stock selection

We analyzed FAO-reported annual, country-level catch time series of 1,740 FAO fish stocks (area-country-species triples) meeting the following criteria: marine wild capture fisheries for finfish and invertebrates with taxonomic identification resolved to the species-level and with catch time series ≥ 20 yrs and ≥ 250 mt of median annual catch after trimming years of zero catch from the beginning of the time series. We also excluded: (1) stocks of species that could not be placed into life history categories consistent with the mPRM model (e.g., barnacles, corals, sea cucumbers, sea urchins, starfish, sponges, etc.); (2) stocks of highly migratory species whose population dynamics cannot be described by catch within a single country's exclusive economic zone (i.e., tunas, marlins, and billfish); and (3) stocks targeted by a distant water fleet whose catch time series is unlikely to be representative of total removals from that population (i.e., stocks whose FAO area and EEZ don't overlap were excluded).

S1.1.2 Building the superensemble model

We used a super ensemble model to estimate the status from 1950-2015 for the FAO fish stocks. We developed the superensemble model using simulated fish stocks from (1) and tested the models on a set of simulated stocks withheld from model training and on real fish stocks in the RAM Legacy Stock Assessment Database (2). The simulated stocks in (1) represent a fully factorial set of 5,760 simulated fisheries comprised of three fish life histories, three levels of initial biomass depletion, four exploitation scenarios, two levels of recruitment variability, two levels of recruitment autocorrelation, and two levels of measurement error, with each combination of parameters run through ten stochastic iterations (Table S4). The

RAMLDB is a global database of catch data and stock assessment output, including reference points and time series of biomass and fishing mortality.

The superensemble model uses boosted regression trees (BRT) to estimate stock status (B/B_{MSY}) from the B/B_{MSY} estimates of four individual catch-only assessment models (Table S1) and two spectral properties of the catch time series. The estimate of B/B_{MSY} in year t uses (i) B/B_{MSY} predictions for year t from all four models (Table S1). Boosted regression trees combine regression and machine learning, offer predictive power superior to other modeling methods (3), and produced the best superensemble model in (4). We excluded SSCOM, one of the individual catch-only models included in the original publication (4) because of its enormous run-time (<8 stocks / day), and included OCOM, which was developed after the model in (4) was published. We included the 0.05 and 0.20 spectral densities of the scaled catch time series (catch divided by maximum catch) because they were shown to improve predictive performance in (4). Because B/B_{MSY} is a ratio bounded at zero, we fit the BRT models using the log of B/B_{MSY} and exponentiated predictions from the model. Thus, each of the superensemble models has the following conceptual structure:

$$\log \theta = f(\beta_{CMSY-17}, \beta_{COMSIR}, \beta_{OCOM}, \beta_{mPRM}, SD_{0.05}, SD_{0.20}) \quad (1)$$

where θ represents the superensemble estimate of B/B_{MSY} , β 's represent the individual model estimates of B/B_{MSY} , and SD 's are the spectral densities of the scaled catch time series.

We divided the simulated stocks for model training (90% of data) and testing (10% of data) by withholding the 10th iteration of each simulation scenario. The training stocks were used to fit the BRT model while the test stocks were used to independently evaluate the model's predictive ability. A grid search for the BRT model parameters that minimize the RMSE using repeated 10-fold cross validation found the following optimal parameters: learning rate=0.005, interaction depth=10, and number of trees=7500. The BRT models were fit using the caret (5) and gbm (6) packages in R v.3.4.2 (7). The model exhibits substantially higher accuracy and lower bias than other catch-only models both in the terminal year (Figure S2) and through time

(Figure S3). The ensemble model's performance increases through time and performs especially well during the final 20- years of the 60-year time series (Figure S3). This is promising because we evaluate the relationship between seafood trade and stock status from 1995 to 2015.

S1.1.3 Assigning life history traits to the FAO species

In addition to catch time series, the individual catch-only models require information on life history category, resilience, and natural mortality. We collected this information using a combination of FishBase (8), SeaLifeBase (9), and FishLife (10) life history information.

We used the *rfishbase* package in R (11) to correct the taxonomy of species in the FAO landings data and download their habitat types, Von Bertalanffy growth parameters, maximum size, and vulnerability and resilience for finfish from FishBase (8) and for invertebrates from SeaLifeBase (9). We also used the *FishLife* package in R (10) to estimate natural mortality and Von Bertalanffy growth parameter for all finfish species. *FishLife* uses a multivariate model trained on FishBase to predict eight life history traits for >32,000 fish (10).

We classified species into the 17 life history categories used by the mPRM catch-only model based on taxonomy using Table S2. We classified species into resilience categories (Table S3) using, in order of preference, resilience values: (1) reported on FishBase/SeaLifeBase; (2) derived from the FishLife Von Bertalanffy K parameter; (3) derived from the FishBase/SeaLifeBase Von Bertalanffy K parameter; (4) derived from the FishBase/SeaLifeBase vulnerability metric; (5) derived from the FishBase/SeaLifeBase Von Bertalanffy maximum age; (6) derived from the genus mode; or (7) derived from the family mode (Table S3). We used natural mortality estimates in the following order of preference: (1) FishLife values; (2) FishBase/SeaLifeBase values; or (3) derived using the t_{\max} - and growth-based estimators recommended by (12). Resilience and natural mortality estimates remained unavailable for only 37 and 64 invertebrate species, respectively (of >1,500 species).

S1.2 Trade data

We used a preprocessed version of the UN's Comtrade International Trade Statistics Database (13) entitled BACI dataset (14). UN Comtrade contains self-reported, national annual import and export bilateral trade flows of 65 seafood commodity groups (corresponding Harmonized System, HS, codes from 1992). Since UN Comtrade contains both importer and exporter reported trade volumes, and these may differ, CEPII developed procedures to reconcile differences in reporting. More details on the processing done in the BACI dataset can be found in a CEPII working paper (15). From this database, we constructed global seafood trade networks for specific species groups (Table S6) following best practices identified by (16). Species groups were specified by commodity group and contained taxonomic class-, family-, genus-, and species-level classifications. We included only seafood products destined for human consumption (selected from HS codes 03 and 16) during 1995-2015.

Although the Comtrade data provides information on the amount and value of seafood product trades between nations, it does not necessarily represent the fish products' geographical origin being traded. For example, seafood products caught in one country could be processed in another country and then exported again (17, 18). For this reason, we excluded all exports explicitly labeled as re-exports and all exports of species groups exported by a country that did not land the same species group in its capture fisheries (section 2.3.). Finally, HS commodity groups do not differentiate between wild capture and aquaculture landings. Therefore, we excluded all species groups that accounted for more than 5% of global aquaculture production (19) and conducted sensitivity analyses around this cutoff to ensure our results' robustness based on the choice of the cutoff fraction (SI 6).

S1.3 Data matching

We used a three step matching process to connect the UN Comtrade data with the stock status estimates. First, we used FishStat to generate a combined FAO trade and UN Comtrade dataset. This matching was based on FAO trade commodity groups and 2012 HS code groups (20).

Second, we matched FAO trade data to the stock status estimates. We used FAO trade commodity group descriptions with common and scientific name specifications to describe species in the stock status estimates to guide the dataset matching. Matchings between commodity groups and scientific names were first done at the species-level. For example, stock status estimates for European plaice (*Pleuronectes platessa*) were matched to commodity group categories such as 'Plaice (*Pleuronectes platessa*), fresh or chilled', and 'Plaice (*Pleuronectes platessa*), frozen'. When the commodity group category was not specified at the species-level, the next level of taxonomic resolution would be matched to the stock status estimates (which are always at the species-level). For example, stock status estimates for American lobster (*Homarus americanus*) were matched to the commodity group category 'American/European lobsters (*Homarus* spp.), meat or tails, fresh or chilled'. When stock status estimates could only be matched to commodity groups of higher taxonomic resolution than class (e.g., 'Fish livers and roes, frozen'), we excluded the stock from the dataset. There was no suitable commodity group for 337 species, and their corresponding stocks (N = 997) were excluded from the dataset.

Finally, the UN Comtrade time series started in 1995. Therefore, we matched the HS 2012 to the HS 1992 codes using correspondence tables. The HS 1992 contains commodity groups such as 'Plaice, frozen, whole'. In this example, we clustered all commodity groups in the species group 'plaice' (Table S6). This last step leads to a loss in taxonomic resolution of the stock status estimates. Therefore, in our final dataset, species groups contain an average of 1.5 stocks per exporter from the stock status estimates and a total of 746 stocks. For example,

we averaged the stock status of red king crab (*Paralithodes camtschaticus*) and blue swimming crab (*Portunus armatus*) in the species group ‘crab’. However, we note that these species share similar life histories, are generally market substitutes, and are often targeted in the same fishery (and therefore experience a common fishing effort), making averaging status a reasonable measure of species group-level fishing impacts. We clustered commodity groups to species to a total of 27 species groups, of which we used 25 for the main analysis corresponding to a 5% cut-off for aquaculture species (SI 6).

S2. GMM estimations validity and robustness

In the GMM estimations we included 2- to 5-year lags of the covariates (i.e. current network indicators) as GMM-type instruments in the GMM estimator (Arellano–Bond estimator). Using instruments can account for reverse causality, resulting in an unbiased (valid) estimation of the effects of network patterns on stock status (21). GMM-type instruments are lags of endogenous covariates and differ from standard instruments (which are always strictly exogenous) used in regression analysis. They are perceived as valid instruments because it is plausible that current disturbances in stock status cannot influence past network characteristics. The number of GMM instruments is less than the number of country and species groups, which avoids issues resulting from having too many instruments (22).

There are several potential sources of correlations between covariates and the error term (referred to as endogeneity). First, one source of endogeneity is the correlation between network indicators and time-invariant fixed effects such as unchanged institutional and geographic characteristics. We used first differencing in the GMM estimations to eliminate country and species group time-invariant fixed effects. Second, time-variant factors in the error term may correlate with network indicators. Using time lags of the covariates as GMM-type instruments in the GMM estimator addressed this problem (22). Finally, common time trends in the dependent variables and covariates can give faulty results. In one of the GMM

estimations, we use year dummies. They can absorb the effects of network characteristics if there are common trends in the latter and little variation around the trends.

S3. Additional GMM estimations

GMM model estimations for the contemporaneous model (Within-Estimator) without lagged dependent variables (Model 3) and with year dummies (Model 4).

The model setting is static and the network effects on fishery stocks are assumed to be contemporaneous. It assumes the functional form described in equation 2 (Table S7, Model 3):

$$\frac{B}{B_{MSY}}_{git} = \lambda + \beta_1 modularities_{gt} + \beta_2 clustering_{gt} + \beta_3 degree_{gt} + \beta_4 trade\ duration_{git} + \varepsilon_{gt}$$

$$where \varepsilon_{gt} = u_{ig} + v_{igt} \quad (2)$$

Where stock status (B/B_{MSY}) of species group g exported by exporter i in year t is predicted by the network level metrics (clustering and degree) and trade duration of species group g in year t . The error term is composed of two terms: first, u_{ig} represents unobserved exporter-species time-invariant fixed effects, and, second, v_{igt} represents a stochastic error term to introduce variation in other variables that could potentially affect stock status but are not included in our model.

The second static model specification is represented by (Table S7, Model 4):

$$\frac{B}{B_{MSY}}_{git} = \lambda + \beta_1 modularities_{gt} + \beta_2 clustering_{gt} + \beta_3 degree_{gt} + \beta_4 trade\ duration_{git} + \gamma_t$$

$$+ \varepsilon_{gt}$$

$$where \varepsilon_{gt} = u_{ig} + v_{igt} \quad (3)$$

878 Above equation includes $(t - 1)$ year dummies (γ_t), which captured the year-specific factors
879 common to all exporter-species pairs. Year dummies, are used to remove time trends in
880 dependent and independent variables but can be negligible if there are no common trends for
881 each species group or each exporter' stock.

882

883 The term v_{igt} might be correlated with other covariates and thus leads to biased estimation.

884 The endogeneity resulting from v_{igt} can be addressed using the GMM estimator.

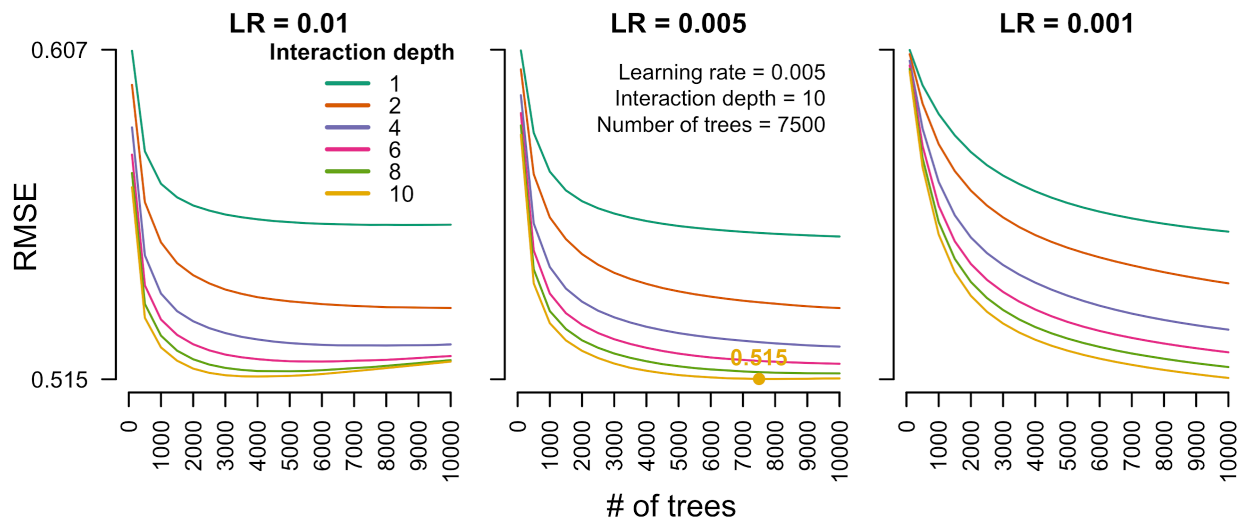


Fig. S1. Model tuning curves showing the average root mean square error (RMSE) for each combination of candidate BRT model parameters (learning rate, interaction depth, # of trees) for the superensemble model. The optimal combination of model parameters (marked and labeled) is the combination that minimizes the RMSE.

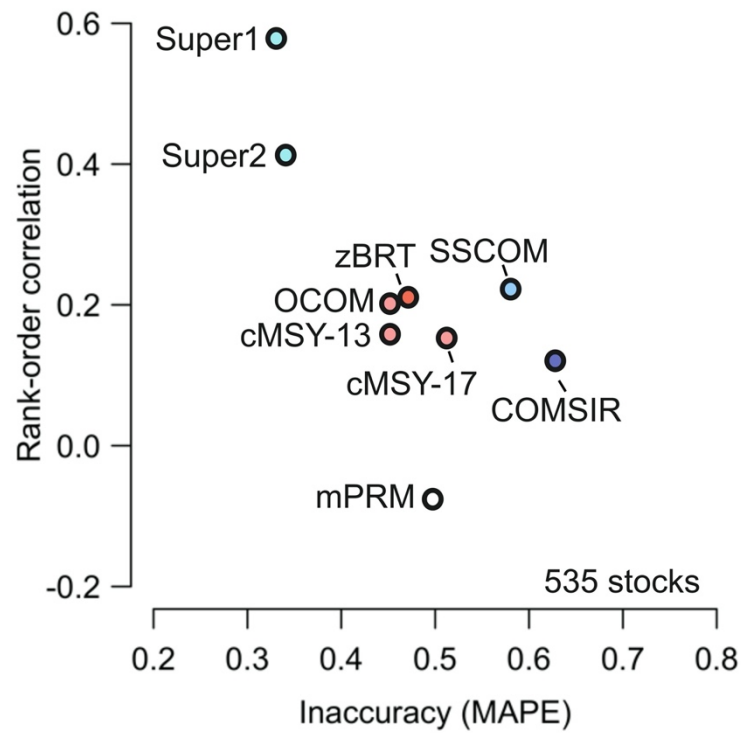


Fig. S2. The performance of COMs evaluated on the simulated stocks withheld from the BRT model training ($n=535$). The best performing methods are indicated by high rank-order correlation and low inaccuracy (top-left corner).

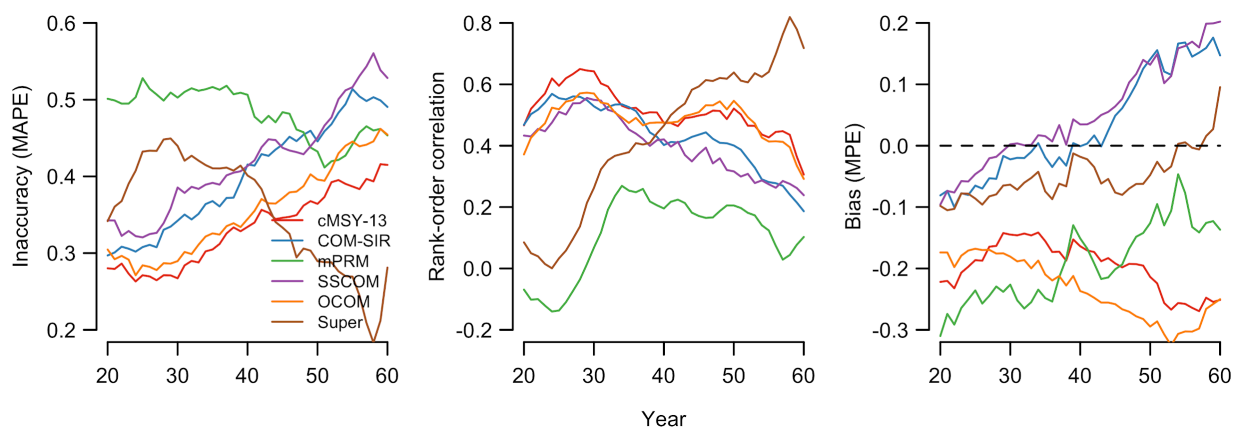


Fig. S3. Status estimation performance of six catch-only stock status models. The performance of the superensemble model improves over time while the performance of the other catch-only models degrades over time.

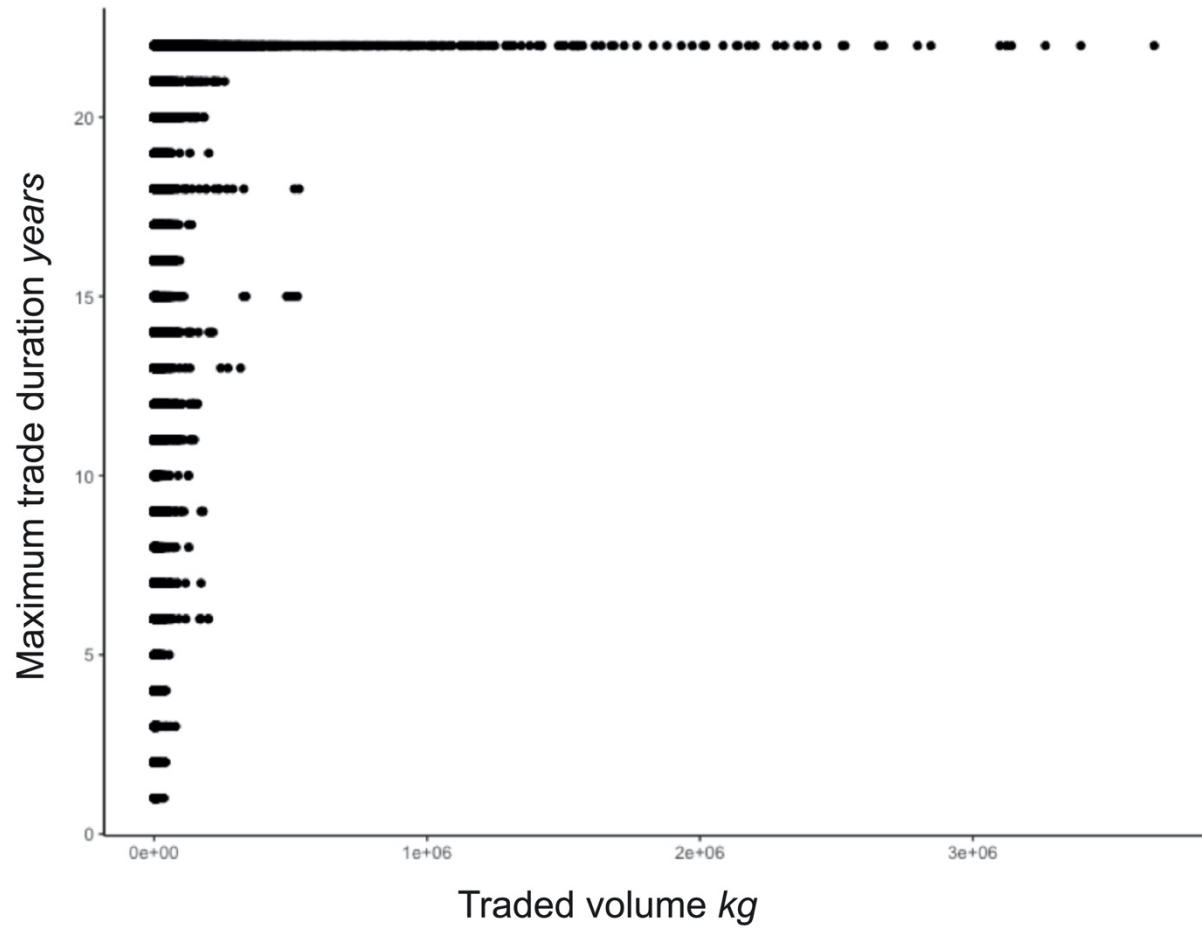


Fig. S4. Shows traded volume and trade duration by exporting country. Traded volume sums all reported trades per year, species group and exporter-importer pair. To calculate maximum trade duration, each consecutive year of trade between an exporter-importer pair is summed.

Table S1. Individual catch-only models used in the superensemble model.

	Method	References	Data input/output	Brief description
1	cMSY-2013 Catch-MSY	(1, 23)	In: Catch, resilience Out: B/BMSY, MSY, B, BMSY	Uses a stock reduction analysis with priors for r , k , and initial/final year depletion derived from resilience to estimate status
2	COM-SIR Catch-only-model with sampling- importance- resampling	(1, 24)	In: Catch, resilience Out: B/BMSY	Uses a coupled harvest- dynamics model fit using a sampling-importance- resampling algorithm to estimate status
3	OCOM Optimized catch- only model	(25)	In: Catch, natural mortality (M) Out: Saturation, MSY	Uses a stock reduction analysis with priors for r and final year depletion derived from M and saturation from Zhou-BRT to estimate status
4	mPRM Modified panel regression model	(4, 26)	In: Catch, taxonomic group Out: B/BMSY	Uses a panel regression model trained on the RAMLDB to predict status from characteristics of the catch time series and taxonomic group

Table S2. Classification of FAO stocks into life history categories consistent with the mPRM catch-only model.

Type	Category	Taxonomic groups
Finfish	Cods, hakes,	Order: Gadiformes
	haddocks	
Finfish	Flounders, halibuts,	Order: Pleuronectiformes
	soles	
Finfish	Herrings, sardines,	Order: Clupeiformes (except the shads)
	anchovies	
Finfish	Shads	Subfamily: Alosinae; Genera: Alosa, Brevoortia, Ethmalosa, Ethmidium, Gudusia, Hilsa, Tenualosa
Finfish	Tunas, bonitos,	Scombridae (tunas, bonitos, mackerel), Istiophoridae (marlin), Xiphiidae (swordfish)
	billfishes	
Finfish	Sharks, rays,	Classes: Elasmobranchii (sharks, rays, skates, sawfish), Holocephali (chimaeras)
	chimaeras	
Finfish	Miscellaneous	Unclassified finfish/cephalopods with w/ a reef-associated, benthopelagic, pelagic-neritic, or pelagic habitat type
	coastal fishes	
Finfish	Miscellaneous	Unclassified finfish/cephalopods with w/ a demersal, bathydemersal, or bathypelagic habitat type
	demersal fishes	

Finfish	Miscellaneous	Families: Salmonidae (salmon), Moronidae (temperate
	diadromous fishes	basses)
Finfish	Miscellaneous	Unclassified finfish/cephalopods with w/ a pelagic-
	pelagic fishes	oceanic habitat type
Molluscs	Abalones, winkles,	
	conchs	Class: Gastropoda
Molluscs	Clams, cockles,	Orders: Veneroida (clams/cockles), Arcoida (ark shells)
	arkshells	plus Myoida (other clams), Mytiloida (mussels)
Molluscs	Scallops, pectens	Order: Ostreoida
Crustaceans	Crabs, sea-spiders	All crab/sea spider families plus geryon families
Crustaceans	King crabs, squat-	Families: Lithodidae (king crabs), Galatheididae (squat
	lobsters	lobsters)
Crustaceans	Lobsters, spiny-	Families: Nephropidae (true lobsters), Palinuridae
	rock lobsters	(spiny lobsters), Scyllaridae (slipper lobsters)
Crustaceans		All shrimp/prawn families plus krill/seabobs/mantis
	Shrimps, prawns	shrimp families

Table S3. AFS and FishBase guidelines for using life history traits to classify the resilience of fish stocks to exploitation and the r priors used by COM-SIR and cMSY-13 for each resilience category.

Resilience	r prior	Von B K (1/yr)	Age at maturity (yr)	Maximum age (yr)	Fecundity (1/yr)
High	[0.6, 1.5]	>0.3	<1	1-3	>10,000
		0.16-			
Medium	[0.2, 1.0]	0.30	2-4	4-10	100-1000
	[0.05,	0.05-			
Low	0.5]	0.15	5-10	11-30	10-100
	[0.015,				
Very low	0.1]	<0.05	>10	> 30	<10
Unknown	[0.2, 1.0]	-----	-----	-----	-----

Table S4. Factorial design of the simulated stocks in (1).

Factor	# of levels	Levels
Life history	3	Demersal, small pelagic, or large pelagic
Initial biomass depletion	3	100%, 70%, or 40% of carrying capacity
Exploitation dynamics	4	Constant, biomass-coupled, increasing, or roller coaster rates
Recruitment variability	2	Low or high variability
Recruitment autocorrelation	2	With or without autocorrelation
Catch measurement error	2	With or without catch measurement error
Time series length	2	20 or 60 years
Iterations	10	Iterations for each combination of the above parameters
Total # of stocks:		5760

Table S5. Indicators of connectivity and duration in seafood trade.

Network characteristic	Calculation	Reference
<i>Modularity</i>	$Q = \left(\frac{1}{2m}\right) * \sum ((A_{ij} - K_i * K_j / 2m))$ <p>Where m is the total of the weights in the graph, A_{ij} is a particular edge between node i and j in the network (More formally, the element of the A adjacency matrix in row i and column j), k_i is the degree of i, k_j is the degree of j, c_i is the type (or component) of i, c_j that of j, the sum goes over all i and j pairs of vertices. Edge weights are considered as the element of the A adjacency matrix, and k_i is the sum of weights of adjacent edges for vertex i.</p>	(27)
<i>Clustering</i>	$C = v/L$ <p>where v is all closed network triangular trade connections and L is the number of triangular trade connections that are possible in the network.</p>	(28)
<i>Degree</i>	$\Sigma u/n$ <p>where u is the number of trade connections of a specific importer or exporter and n is the number of countries in the network.</p>	(29)
<i>Trade duration</i>	$\Sigma d/l$ $d = \begin{cases} 1 & \text{if } D \geq 3 \\ 0 & \text{if } D < 3 \end{cases}$ <p>where D is the number of consecutively traded years between a specific importer and exporter pair and l is the number of importers trading with the specified exporter.</p>	-

Table S6. 27 species groups included in the analysis (listed alphabetically). Species groups excluded under different scenarios are listed in Table S8.

Species groups
Anchovies
Coalfish
Cod
Crab
Cuttlefish
Eel
Flatfish
Haddock
Hake
Halibut
Herring
Homarus
Lobster
Mackerel
Mussel
Octopus
Oysters
Plaice
Rock lobster
Salmon
Salmonidae
Sardines
Scallop
Seabass
Shark
Shrimp
Sole

Table S7. GMM model estimations for the contemporaneous model (Within-Estimator) without lagged dependent variables (Model 3) and with year dummies (Model 4). Standard errors in parentheses. Significance levels reported as * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Network Characteristics	Model 3	Model 4
	B/B _{MSY}	B/B _{MSY}
Modularity	-0.0243 (0.0984)	0.00498 (0.0857)
Clustering	0.787*** (0.164)	-0.215 (0.130)
Degree	-0.0175*** (0.00280)	0.00332 (0.00327)
Trade duration	0.0153 (0.0293)	-0.0533 (0.0287)
Year dummies	No	Yes
<i>N</i>	8555	8555
<i>p</i> -value AB test for AR(2)	0.371	0.326
<i>p</i> -value Hansen test	0.297	0.566

Table S8. Species groups excluded from **Table S6** under different thresholds regarding their contribution to global aquaculture production in volume (19).

Threshold 10%	Threshold 5%	Threshold 3%
None	Oysters	Oysters
	Shrimp	Salmon
		Salmonidae
		Shrimp

Table S9. Two-step difference GMM estimations for the contemporaneous model using a 10% threshold. Windmeijer's finite-sample corrected standard errors in parentheses.

Significance levels reported as * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Network Characteristics	Model 5 B/B _{MSY}	Model 6 B/B _{MSY}
Modularity	0.0261 (0.0828)	0.0525 (0.0828)
Clustering	0.225* (0.0968)	0.232* (0.0977)
Degree	-0.00339 (0.00209)	-0.00364 (0.00211)
Trade duration	-0.00392 (0.0269)	-0.000246 (0.0250)
(B/B _{MSY}) _{t-1}	0.567*** (0.0351)	0.565*** (0.0350)
(B/B _{MSY}) _{t-2}	0.139*** (0.0223)	0.145*** (0.0218)
N	6195	6565
p-value AB test for AR(2)	0.769	0.697
p-value Hansen test	0.369	0.331

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