ENVIRONMENTAL STUDIES

Wealthy countries dominate industrial fishing

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The patterns by which different nations share global fisheries influence outcomes for food security, trajectories of economic development, and competition between industrial and small-scale fishing. We report patterns of industrial fishing effort for vessels flagged to higher- and lower-income nations, in marine areas within and beyond national jurisdiction, using analyses of high-resolution fishing vessel activity data. These analyses reveal global dominance of industrial fishing by wealthy nations. Vessels flagged to higher-income nations, for example, are responsible for 97% of the trackable industrial fishing on the high seas and 78% of such effort within the national waters of lower-income countries. These publicly accessible vessel tracking data have important limitations. However, insights from these new analyses can begin to strategically inform important international- and national-level efforts underway now to ensure equitable and sustainable sharing of fisheries.

INTRODUCTION

How nations share access to fish in the oceans significantly influences global food security, wealth distribution, competition between industrial and small-scale fisheries, and even international conflict. Globally, approximately 110 million metric tons of marine wild fish are caught annually, with an estimated annual value of over 171 billion USD for reported and unreported catch (*1*). Approximately 3 billion people receive 20% of their average intake of animal protein from aquatic animals, and in certain countries the per capita intake can be >50% (*2*). Contributions to human health from seafood-derived nutrients other than protein may be even more important. It has been estimated, for example, that 845 million people are currently at risk of experiencing deficiencies of essential micronutrients including zinc, iron, and vitamin A, a number expected to increase if projected declines in fisheries catch potential and per capita fish supply continue into 2050 (*3*). Conflict over fishery resource sharing has also shaped historical patterns of regional stability and promises to continue to do so in the near future (*4*, *5*). The dynamics by which we divide up global fisheries resources also shape competition between large-scale, capital-intense industrial fisheries and small-scale fisheries, with cascading effects upon the health, prosperity, and well-being of the communities that depend on small-scale fisheries (*6*–*8*).

Describing fishing patterns in comprehensive and quantitative terms, both in national waters and on the high seas, is challenging due to the lack of open access to detailed records on the behavior of fishing vessels. However, advances in machine learning technologies and big data capacity now offer us access to high-resolution fishing vessel activity from 22 billion automatic identification systems (AIS) points, processed by the Global Fishing Watch platform using convolutional neural network models (*9*, *10*). We analyzed these data to generate a global, fishery-independent assessment of the amount of industrial fishing effort conducted by vessels flagged to higher-income nations (that is, World Bank categories "high income" and "upper middle income" combined) and lower-income nations (that is, World Bank categories "lower middle income" and "low income" combined). We concentrate this analysis solely on industrial fishing (defined here as all vessels >24 m) (*11*) because industrial fishing is the dominant fishery on the high seas, it is much more readily visible via AIS data than small-scale fishing, and it globally accounts for an estimated 84 million metric tons and 119 billion USD [3.1 times more biomass and 2.3 times more revenue than smaller-scale artisanal fishing (*1*)].

Analyzing and communicating patterns of the distribution of fishing effort by different nations on the high seas are especially timely and important given the immediate opportunity to use these data to shape progress toward a United Nations treaty being developed for biodiversity on the high seas (*12*). Resources on the high seas are unique with respect to their governance, as they have been designated as international resources that are to be cooperatively managed. Currently, fisheries are overseen by regional fishery management organizations, but both geographic and taxonomic gaps in coverage exist (*13*, *14*). New insight derived from these big data analyses of high seas fisheries can help decision makers at the United Nations identify how different policy interventions may affect high seas stakeholders and can highlight which states have the most opportunity and responsibility for the development of this emerging treaty (*14*).

Understanding the distribution of fishing effort in a nation's marine Exclusive Economic Zone (EEZ) is also useful for policy-making, especially in the context of access agreements that allow foreign fishing in a nation's waters. Existing research has highlighted the fact that fleets from higher-income nations travel farther to fish after they deplete their own fish populations, increase their per capita fish intake, or otherwise experience increases in seafood demand (*15*). The increased capacity and improved technology characteristic of higher-income nations have also enabled these countries to build and operate their own distant water fishing fleets, and often to subsidize those fleets heavily (*16*, *17*). Lower-income countries usually lack the same capacity to industrially catch their fish populations and thus frequently enter into fishing access agreements with these wealthier countries, sanctioning foreign fishing within their national waters. There are numerous challenges

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that have been raised concerning the sustainability and equitability of these arrangements. For example, the benefits projected to accrue from these partnerships, such as revenue and investment in local technology and infrastructure, have not always lived up to their promise (*18*–*22*). In addition, lower-income nations have in some cases failed to adequately assess and manage their fisheries, including foreign exploitation (*17*). Addressing any shortcomings in these fishing access agreements has become even more pressing as concerns about food security have increased in the many areas of the world where people are nutritionally dependent on seafood and the sustainability of seafood supply is threatened by overfishing and climate change (*3*, *23*). It is now imperative to have a clear view of who is controlling access to fish within a nation's EEZ and whether fish as food are making it to the food insecure. Quantitative and open assessments of the degree to which foreign fishing occurs, particularly within the waters of lower-income nations, can help diverse stakeholders more thoughtfully engage in national-level conversations about fishery resource sharing.

The AIS-derived measures of fishing effort have proven uniquely insightful. They have been used for marine protected area surveillance (*9*), to examine how environmental variability shapes fishing behavior (*10*), to quantify the overlap between marine wildlife and fisheries (*24*), and to assess the economic costs and benefits of high seas fishing (*25*). However, AIS presently does not detect all industrial fishing effort and has a number of limitations. As a means of quantitatively evaluating these potential biases and gaps, we (i) directly compared differences between fishing activity detected using AIS and traditional national-level published registries of industrial fishing vessels; (ii) compared patterns of fishing effort detected using the open AIS data and closed access proprietary vessel monitoring system (VMS) data voluntarily shared by a lower-income nation, Indonesia, which hosts the largest industrial fishing fleet of all lower-income nations; and (iii) compared our AIS-estimated fishing effort outputs against measures of fishing catch drawn from the Sea Around Us database (including newly updated high seas catch estimates) (*1*, *25*). Our examination of biases using these methods provides a first means to constructively contextualize and cautiously interpret these AIS-derived patterns.

The outputs from our analyses reveal profound heterogeneities in the distribution of AIS-detectable industrial fishing effort. Overall, these results present a valuable quantitative and open opportunity for diverse stakeholders to reexamine a number of important questions surrounding how marine fisheries resources are globally shared. Results such as this may assist in constructively designing policies for marine areas both within and beyond boundaries of national jurisdiction that promote responsible and equitable sharing of the wealth, food, and biodiversity found in our oceans.

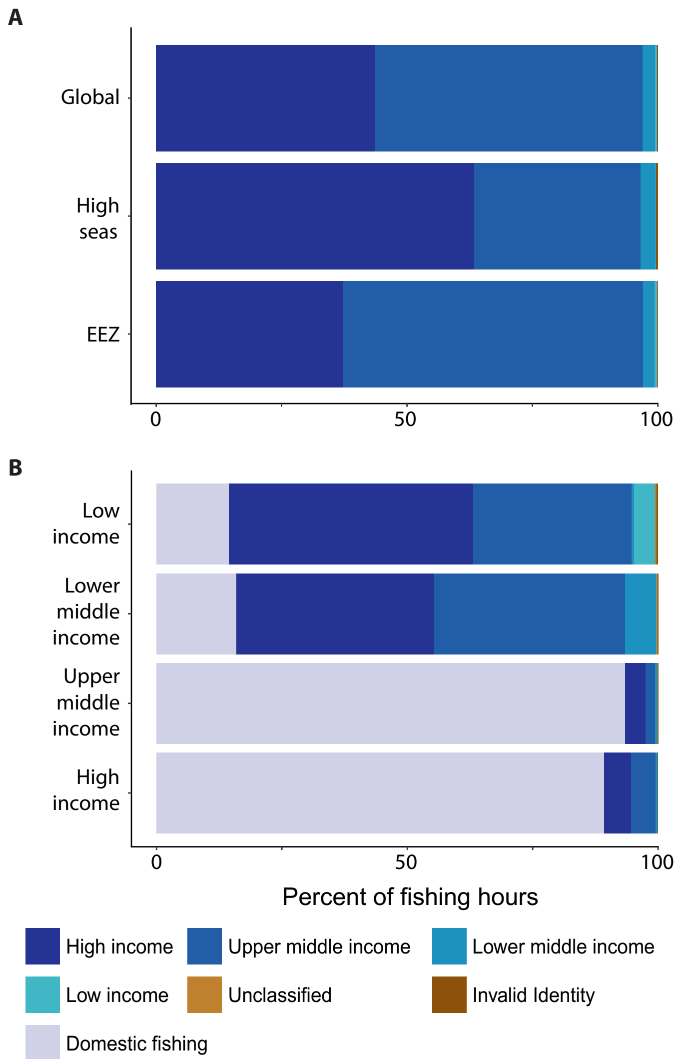

Fig. 1. Distribution of industrial fishing effort by vessels flagged to nations from different income classes as measured using AIS data and convolutional neural network models. (**A**) The percent of fishing effort (measured in fishing hours) detected globally on the high seas and in all EEZs for vessels flagged to nations from four different World Bank income groups. (**B**) The percent of AIS-detected industrial fishing effort in all EEZs, grouped by the World Bank income groups of the EEZs. Here, the category Domestic fishing is included, which refers to instances when a fishing country was fishing in its own EEZ. Other categories represent foreign fishing effort conducted within an EEZ by a nation flagged to one of the four World Bank income classes. "Invalid identity" refers to vessels with a Maritime Mobile Service Identity (MMSI) number that did not accurately refer to an individual country. "Unclassified" refers to fishing entities that were fishing in an EEZ but did not have a World Bank income group. All data presented here are summarized from the year 2016.

RESULTS

High seas

An analysis of all AIS-detectable fishing effort identified on the high seas using convolutional neural networks during the years 2015–2016 revealed that industrial fishing effort was dominated by vessels flagged to higher-income nations, with less than 3% of effort attributed to vessels flagged to lower-income nations (Figs. 1A and 2 and fig. S1A). These patterns remain consistent when each of these years is analyzed individually and when measuring AIS-detectable fishing effort in terms of fishing days rather than fishing hours for 2016 (Fig. 1 and figs. S1 and S2). The spatial distribution of this industrial fishing effort in 2016 was summarized at the global level (Fig. 2) and by ocean basin (fig. S3) and reiterates the spatial dominance of vessels flagged to higher-income countries across the high seas. The majority of all AIS-detectable high seas industrial fishing effort was detected in the Pacific Ocean (61%), followed by the Atlantic Ocean (24%) and the Indian Ocean (14%; fig. S3).

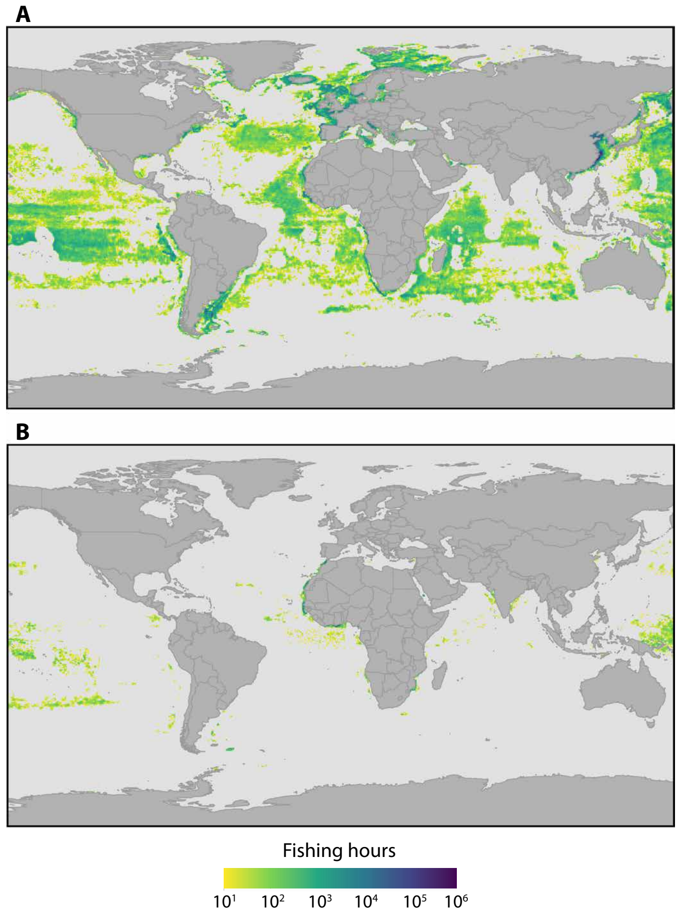

Fig. 2. Density distribution of global industrial fishing effort, derived using AIS data. (**A**) Vessels flagged to higher-income countries and (**B**) vessels flagged to lower-income countries. Industrial fishing effort is estimated using convolutional neural network models and plotted as the $\log_{10}$ number of fishing hours.

National waters

Globally, vessels flagged to higher-income nations made up the vast majority (97%) of all industrial fishing effort detected in EEZs for 2016 (Fig. 1A). In the EEZs of higher-income nations, fishing effort was predominantly attributed to each nation's domestic fishing fleet, making up 89% of fishing effort in high-income EEZs and 93% of fishing effort in upper middle–income EEZs. Conversely, domestic fishing made up very little of the overall fishing effort in lower-income nations. Eighty-four percent of the industrial fishing effort in lower-income EEZs was conducted by foreign countries, with the majority of this industrial fishing effort (78%) from vessels flagged to high- and upper middle–income nations. Most AIS-detectable industrial fishing effort that was observed within all EEZs was detected in the Pacific Ocean and the Atlantic Ocean (60 and 35% of total fishing effort observed in all EEZs respectively; fig. S4). Patterns were consistent across the 2 years studied with nearly identical patterns recorded in 2015 (fig. S1B).

Evaluating gaps and sensitivity of AIS coverage

In an effort to begin to evaluate the level of vessel coverage afforded by the above reported AIS-derived measures of fishing effort, we compared the number of unique industrial fishing vessels categorized as actively fishing in the Global Fishing Watch vessel database to the total number of industrial fishing vessels recorded in the Food and Agriculture Organization of the United Nations (FAO) vessel registry (*10*). During the period of our study, we detected a global total of 30,469 active vessels matching our definition of industrial fishing (that is, >24 m in length). This figure represented 59% of the global total number of fishing vessels >24 m logged in the FAO registry (fig. S5). Alignment of vessel counts between these two data sets was stronger for vessels flagged to higher-income nations than lower-income nations.

When we conducted the same AIS-based analyses including smaller-sized vessels (industrial fishing threshold defined at >12 m instead of vessels >24 m), our conclusion that higher-income vessels dominate industrial fishing on the high seas and within EEZs was only further confirmed (fig. S6). As a means of assessing and potentially adjusting for possible lower AIS detection rates of industrial fishing vessels in lower-income nations, we compared AIS-derived estimates of industrial fishing during 2016 to closed access VMS-derived estimates of industrial fishing from data shared voluntarily by Indonesia. Both the number of individual industrial fishing vessels and the amount of estimated fishing effort were found to be lower in AIS estimates than in VMS estimates for Indonesia (fig. S7). When these calculated AIS/VMS differences for Indonesia were used to create correction factors for lack of AIS vessel visibility for other lower-income nations (see Supplementary Materials and Methods), this increases the amount of projected lower-income fishing effort on the high seas and within the waters of lower-income EEZs (fig. S8). However, even when these VMS-informed corrections are included, these results do not qualitatively change the directionality or bulk conclusions of the patterns reported in the AIS-only results, namely, that vessels flagged to higher-income nations dominate industrial fishing effort on the high seas, within EEZs globally, within low-income EEZs (64%), and nearly dominate within lower middle–income EEZs (48%).

Comparison of AIS-derived fishing effort and reconstructed catch data

When comparing 2016 AIS-derived industrial fishing effort for all vessels >24 m and catch reconstructions from 2014 (most recent year available), we found moderate and variable congruence. In the case of the high seas, the same five top-ranked flag states were listed for both AIS-derived estimates of fishing effort and the newly updated reconstructed catch. The combined activity of these five states on the high seas made up 86.3% of all AIS-derived industrial fishing effort (fishing hours) and 59% of all of the reconstructed catch (metric tons).

In the case of EEZs, we again compared overlap between the vessel flag states on the top five lists for both AIS-measured fishing effort and reconstructed catch data. In 53 such comparisons (table S1), we observed a mean of 2.2 flag states that were present on both lists (that is, 2.2 of 5 possible flag states in common between AIS-measured effort and catch reconstruction top five lists) and a median of two flag states on both lists. In addition to these comparisons, we compared the proportional contribution with respect to amount of AIS-measured fishing effort and reconstructed catch data for flag states that matched on both top five lists. The strength of these matches varied by EEZ income category. In the case of high-income EEZs, flag states appearing on both the top five lists for AIS effort and catch reconstruction data contributed an average of 81% of AIS-detected fishing effort and 85% of the reconstructed catch. In contrast, in low-income countries, these flag states on both top five lists contributed on average 35% of AIS-detected fishing effort and 50% of the reconstructed catch.

DISCUSSION

The new view afforded from this open AIS-based analysis of global fishing activity reveals stark levels of unevenness with respect to wealth class for industrial fishing effort. Globally, 97% of all industrial fishing effort detectable using AIS (on the high seas and within EEZs) comes from vessels flagged to higher-income nations—or 23 million total hours of industrial fishing effort in 2016. This same pattern of dominance by higher-income nations repeats itself on the high seas, within the EEZs of higher-income nations, and within the EEZs of lower-income nations.

On the high seas, 97% of all such fishing effort detectable by AIS is conducted by vessels flagged to higher-income nations. Dominance of this high seas industrial fishing effort at the level of flag nation was highly uneven. The vast majority (86%) of this effort can be attributed to only five higher-income countries/entities, in rank order (high to low; table S2): China, Taiwan, Japan, South Korea, and Spain. When China and Taiwan are analyzed together, they account for approximately 52% of the industrial fishing effort we detected on the high seas, which, by reference, is an amount approximately 12 and 27 times greater than the high seas fishing effort detected for the United States and Russia (two other large nations), respectively. The only two lower-income nations that ranked among the top 20 nations with the highest amount of AIS detectable industrial fishing effort on the high seas were Vanuatu and Ukraine (both lower middle–income nations). Vanuatu is a nation with an open vessel registry (colloquially known as a "flag of convenience") that has been reported to include many vessels owned and controlled by higher-income foreign nations (*26*). The majority of the Ukraine fleet is owned by the Ukrainian government.

We observed strong dominance of vessels flagged to higher-income nations with respect to industrial fishing effort on the high seas in all ocean basins (fig. S2). The majority of the industrial fishing effort we identified on the high seas was observed in the Pacific Ocean, a pattern likely reflecting the intensity of tuna fisheries in the Pacific. Overall, these AIS-derived estimates for the distribution of industrial fishing effort on the high seas are qualitatively similar to other estimations created by key actors tracking industrial fishing on the high seas. For example, quantitative assessments of fisheries landings and estimations of the value of these landings likewise suggest that wealthy nations dominate fisheries resources on the high seas (*27*).

Very similar dominance patterns were reported in our analysis of the world's EEZs, where the majority of AIS-detectable industrial fishing effort within national waters was executed by vessels flagged to higher-income nations. We emphasize, however, that a strongly divergent pattern emerges from our analyses of fishing effort density within the EEZs of higher- and lower-income nations. The vast majority of AIS-detected fishing effort within the EEZs of higher-income countries came from their own fishing fleets (Fig. 1). Nearly the inverse was true for lower-income nations, where foreign fishing vessels (mostly flagged to high- and upper middle–income countries) dominated the industrial fishing effort in their EEZs. Most of the industrial fishing effort in lower-income EEZs was conducted by foreign countries, with the majority of this effort from vessels flagged to high- and upper middle–income nations. As an example of this dichotomy, the vast majority of the AIS-detected industrial fishing in high-income Spain's EEZ (96%) was recorded from vessels flagged to Spain. In contrast, in low-income Guinea-Bissau, the vast majority of the industrial fishing effort we detected came from foreign flagged vessels (95%), including 45% from Spain (table S1). Globally, the three countries showing the greatest fishing activity in other nations' EEZs were (from high to low) China, Taiwan, and South Korea. China and Taiwan together accounted for 44% of this global foreign fishing (table S3). We detected fishing effort from China alone in the marine waters of approximately 40% of all non-landlocked nations ($n = 60$ distinct EEZs). China, Taiwan, and South Korea (from high to low) also carried out the highest amounts of foreign fishing effort recorded globally in lower-income EEZs, or approximately 63% of all such effort detected (table S4). There are certainly exceptions to the bulk pattern of higher-income dominance of fishing effort in lower-income EEZs. In some lower-income nations, such as India, there was virtually no detectable higher-income fishing within their EEZs. These patterns may be explained in part by national legislation prohibiting or limiting foreign fishing within such EEZs, but could also result from joint fishing regimes occurring within these EEZs.

The patterns of industrial fishing effort within EEZs derived using these AIS-based techniques reinforce and extend conclusions drawn elsewhere using other methodologies and data sources. For example, analyses of fisheries production and trade data reveal a persistent trend whereby wealthy nations fish in the waters of less wealthy nations, but not vice versa (*28*, *29*). The relatively recent emergence of the capacity to track industrial fishing effort using AIS prevents examination of the history of this buildup. Elsewhere, however, it has been suggested that the ascendancy in dominance of more wealthy nations fishing within the waters of less wealthy nations (for example, Europe in Northwest Africa) has occurred within the last several decades (*28*).

Our AIS-derived estimates of industrial fishing effort agree, in some but not all instances (table S1), with published catch reconstruction data (*1*). Differences in governance appear to explain some of the deviation between these two data sources. For example, in high-income nations in the European Union, where laws and enforcement of AIS regulation in national waters are strong and compliance is expected to be high, we see high congruence among the top five countries in AIS and catch reconstruction estimates of fishing activity, and these top-ranked countries often contributed the vast majority of the overall effort (table S1) (*10*). However, in lower-income nations where enforcement of AIS regulations is sometimes, but not always, lacking, there were many examples of poor alignment. In Sierra Leone's EEZ, for example, vessels from Italy and China were the top rank–ordered fishing entities recorded using AIS, making up 90% of this fishing effort, while reconstructed catch data estimated that the two most active nations, Sierra Leone (domestic fishing) and Russia, caught 93% of the total catch. Explanations for this discrepancy include the following: that industrial fishing vessels flagged to Russia and Sierra Leone were not transmitting AIS; that cancellation of a World Bank project in the region that occurred during this period may have reduced capacity for monitoring, control, and surveillance (MCS) activities (*30*); an increase in illegal fishing displaced from Guinea's EEZ to the north due to increased MCS there (*31*); that top nations observed fishing using AIS (for example, Italy and China) were not reporting catch; or that there is extreme year-to-year volatility in the players involved in industrial fishing in Sierra Leone, which complicates comparisons of the 2014 catch data to the 2016 AIS-derived effort data. The difficulty of interpreting year-to-year volatility in Sierra Leone fishing activity was further increased by the Ebola outbreak that occurred in the region during this period, which necessarily diverted attention from traditional fisheries reporting and enforcement efforts and may have accelerated levels of foreign fishing (*30*). Another general explanation for some of the observed deviations between the AIS and catch reconstruction measures of industrial fishing in other contexts may derive from the fact that the catch reconstruction data will, in some cases, reassign catch from vessels flagged to a particular country to the nation of origin or ownership for the vessel. In the Seychelles, for example, catch from Seychelles-flagged, foreign-owned vessels was assigned in the catch reconstruction data to these foreign countries or to the category "unknown fishing country." A large portion of the catch in the unknown countries category is likely to be from Spain, as large Spanish fishing companies own Seychelles-flagged fishing vessels or otherwise operate in the Seychelles under access agreements. Although three of the five top fishing nations were listed in both the AIS and catch reconstructed measures for the Seychelles, the amount of effort attributed to each nation varied. In the AIS measure of fishing effort within the Seychelles EEZ, Taiwan was responsible for 64% of the observed fishing effort followed by the Seychelles-flagged fleet with 25% of the observed fishing effort. Meanwhile, the catch reconstruction data listed "unknown fishing country" for 68.8% of all catch in the Seychelles, followed by Taiwan at 20%; the Seychelles-flagged fleet was listed in fourth place, responsible for 0.4% of all catch in their own EEZ.

In these AIS-based analyses of fishing effort, we did not attempt to differentiate between legal and illegal fishing effort. We wish, however, to directly call attention to the fact that illegal and unreported fishing constitutes an important fraction of the global industrial fishing effort that occurs worldwide. For example, by some estimates, IUU (illegal, unreported, and unregulated) fishing has historically accounted for, on average, 18% of global catch (*32*). Determining, however, which of the vessels that we tracked in this analysis using AIS were legally permitted to fish in any given domain of ocean is hampered by a lack of transparency and disclosure for many fishing access agreements (*19*). Furthermore, while some illegal fishing is detectable using AIS data (*14*), certainly much illegal and unreported industrial fishing is conducted by vessels lacking or improperly using AIS [often in contravention of International Maritime Organization (IMO) and national maritime regulations] and cannot be tracked. It is difficult to predict exactly if and how inclusion of illegal and unreported fishing behavior would affect the patterns we report. Many high-profile cases have been noted of higher-income nations illegally fishing in lower-income EEZs (for example, European and other more wealthy states illegally fishing in West Africa) (*30*). However, illegal fishing is perpetrated by vessels flagged to both higher- and lower-income nations.

Given our direct focus on industrial fishing, this analysis wholly omits any consideration for patterns of catch by artisanal or other small-scale fishing fleets. The focus on industrial fishing in this analysis should not be meant in any way to discount the importance of small-scale fisheries, particularly the vital role they play in coastal community health and food security. For example, it has been estimated that small-scale fisheries may contribute between 25 and 30% of global catch (*33*) and are the source of a large fraction of fish that make it into the diets of local and regional communities. The patterns that we highlight of extensive industrial fishing from vessels flagged to foreign wealthy nations in the EEZs of less wealthy nations are likely to directly affect the future of many artisanal fisheries. It is known in many regions that industrial fisheries can outcompete smaller-scale artisanal fishing, a potentially undesirable outcome in areas where small-scale fisheries use less fuel, are less ecologically damaging, and provide more food and jobs to local communities (*6*–*8*).

Our analysis also does not differentiate between gear types used by industrial fishing vessels. Self-reporting of gear type in AIS data suggests that our pooled analysis of global industrial fishing is dominated numerically (that is, proportion of unique vessels) by trawlers, purse seiners, and longline vessels. Certainly different gear types fish in different ways, which may complicate our estimations of fishing effort made using fishing hours; for example, the extreme time efficiency of purse seiners setting rapidly upon fish aggregating devices is not comparable to more time-intensive fishing methods, such as longline fishing. To investigate the sensitivity of our conclusions to this choice of fishing hours as our currency of measure for fishing effort, we reanalyzed our data measuring fishing effort in the time currency of fishing days. Effort analyses made using fishing days did not change the direction or pattern of our major conclusions for the high seas or within national waters (fig. S2).

We highlight here three major shortcomings of using AIS. First, international and national regulations for the use of AIS and enforcement of these regulations are insufficient in many parts of the high seas and in many EEZs. Many countries adhere to IMO requirements on AIS usage; however, the specifics by which these regulations are codified into national law vary widely, with examples of strict and lax regulation found among both higher- and lower-income nations (see table S5) (*9*). Second, industrial fishing vessels in lower-income nations may be less likely to carry and use AIS for reasons unrelated to AIS policy. We note that we detected fewer vessels using AIS than are represented on FAO vessel registries and that there is less AIS visibility for vessels registered to lower-income nations (fig. S5). There are a variety of explanations for these discrepancies. For example, some vessels listed by the FAO may have been inactive during our study or regional officials may have overreported fleet sizes to emphasize local growth. By using VMS data derived from Indonesia, we were able to conservatively estimate upper bound corrections for AIS underreporting in lower-income nations (figs. S7 and S8). This correction, however, only increases the global contribution of lower-income fishing on the high seas by approximately 6% and within the EEZs of lower-income nations by 29%. A third potential weakness of AIS stems from reliance on a vessel's reported maritime identification digits (MID) to identify flag state. These MID are typically self-reported and may be entered incorrectly. This also relates to the larger, well-known problem of flag states not always corresponding to the state of vessel control or owner residence [rates estimated at 22.4% based on one analysis (*26*)], as many vessels operate with flags of convenience to take advantage of lower operational costs, less regulation, and reduced tax liability (*26*, *34*). Consequently, many vessels that we class in this analysis as flagged to lower middle– or low-income nations may actually have economic ties that are more closely aligned with higher-income nations. A related important nuance not treated in our analysis is that we do not track the actual firms or companies that own or fund the vessels observed through AIS, despite the influence that these firms have over vessel behavior.

Collectively, some of these uncertainties and potential biases inherent to AIS data may act to overestimate fishing effort from higher-income nations (for example, reduced visibility of smaller vessels from lower-income nations), and some may act to underestimate higher-income nation fishing effort (for example, a large number of vessels originating from higher-income nations flagged to lower-income nations known as flags of convenience). Our general conclusion that vessels flagged to higher-income nations dominate industrial fishing on the high seas and within EEZs largely persisted when we aggregated effort by day instead of fishing hour (fig. S2), retested our conclusions using a smaller size threshold (that is, >12 m) for defining industrial fishing vessels (fig. S6), and added a VMS-informed correction for undetected fishing effort in lower-income nations (figs. S7 and S8). Nevertheless, responsible interpretation of the new patterns we report using AIS requires direct consideration of all the aforementioned potential weaknesses and uncertainties.

These AIS-based analyses find that vessels flagged to higher-income nations dominate industrial fishing within the EEZs of lower-income nations. This observation requires explicit consideration in the analysis of development policy and strategy where fisheries governance intersects with food and nutrition policy, trade policy (export promotion, import substitution), wealth creation and economic growth, job creation, and technological innovation. There has been considerable productive and healthy debate concerning how the dominance of higher-income fishing in lower-income nations EEZs shapes these agendas (*19*, *21*, *28*, *35*). These perspectives are diverse and sometimes conflicting.

On one side, many researchers and managers have expressed unease concerning the potential vulnerabilities that may be created by concentrating dominance over fisheries in the hands of a few wealthy nations. These groups sometimes refer to this skew in control over marine resources as "ocean grabbing" or "marine colonialism" and connect the potential risks involved to those often associated with the practices of land or resource grabbing that occurs when wealthy foreign nations or foreign companies take control of terrestrial or agricultural resources or infrastructure in less-wealthy nations (*36*). Concerns in these discussions about food sovereignty relate to the rights of local people to control their own food systems, including the ecological dynamics, production pathways, and markets underpinning these systems (*37*). These issues are particularly pronounced in nutritionally sensitive areas like West Africa. Guinea, a low-income nation that is heavily reliant nutritionally on seafood, presents an apt example. Approximately 75% of Guinea's population (an estimated 10.1 million people) may be vulnerable to micronutrient deficiencies in future scenarios with reduced access to seafood, making it one of the most nutritionally vulnerable countries in the world to losses of seafood (*3*). In this analysis, we estimate that over 80% of the industrial fishing effort we detected in Guinea's EEZ came from China (table S1), a situation that presents potential challenges. Many argue that a rights-based approach focusing on the human right to adequate food would lead to greater retention of important nutritional resources in lower-income nations, ensuring healthier diets, reduced rates of malnutrition, and increased access to foods of cultural importance (*38*). Significant concern has also been raised about how corruption in some lower-income nations may facilitate misuse of fisheries access payments that prevent such cash from constructively aiding health, development, and growth goals of these nations (*17*, *19*–*21*). Policy options for meeting rising demand for fish in the Pacific region include actions such as diverting some of the tuna currently exported (and captured mostly by foreign fishing vessels) onto domestic markets of lower-income states (*39*). Another possible opportunity for intervention for stakeholders concerned about foreign dominance of industrial fishing in their national waters derives from the open nature of the data we report and the transparency it fosters. Access to these publicly accessible data feeds creates opportunities for all citizens in lower-income nations to put meaningful questions to their local leaders regarding sanctioned and unsanctioned foreign industrial fishing in their home waters.

Others have argued that allowing higher-income nations to dominate fisheries presents a desirable and efficient pathway for developing nations to turn their natural capital (for example, fish resources) into financial capital (for example, access fees, license fees, taxes, foreign exchange earnings). Building up a domestic industrial fishing fleet, maintaining it, and servicing it require port infrastructure, a trained workforce, processing and handling capacity, and considerable financial capital—all of which can be challenging to mobilize or lacking in many fish-rich lower-income countries. Kiribati provides an example of a country where arguments have been made for the efficiency of translating fish into cash. Kiribati is a lower middle–income nation for which we determined that 99% of the industrial fishing effort within its EEZs was delivered by foreign flagged vessels, with the majority of this effort (91%) coming from higher-income nations. Kiribati reported generating 121.8 million USD in 2016 by selling access to fishing rights in its EEZs, with similarly substantial revenues collected in surrounding years (*39*, *40*). Generally, it is not entirely clear that allowing industrial fisheries from wealthier countries to dominate offshore fisheries within less-wealthy nations' EEZs always has negative food security impacts. The efficiencies of industrialized fisheries allow them to put large quantities of lower-cost fish onto the global market, and this results in a net import of lower-priced processed fish from wealthier nations to poorer nations that, in terms of overall per-capita supply, may help counterbalance the net movement of higher-priced fish from poorer to richer countries (*35*, *41*). Much of the lower-value fish that is eventually exported back to lower-income nations are small pelagic fish that are particularly nutrient rich (for example, canned anchovetas, sardines, herrings, and mackerels), and while there is concern that an increasing proportion of these fish are going toward aquaculture and livestock feeds (*42*), this may represent an important nutritional benefit to developing countries. The global industrial fishing fleet thus plays a part in maintaining and enhancing the contribution of fish to meeting micronutrient requirements in lower-income populations in developing economies (*35*).

The capacity to view and analyze large portions of publicly accessible data that reveal how the world divides up a major global resource, like marine fish, is unique. Analogous sources of detailed insight are not, unfortunately, available for other environmentally, socially, and economically important large transnational resource harvest domains, such as logging or mining. The results presented in this analysis represent data-driven hypotheses surrounding distributions of industrial fishing effort that can be thoughtfully considered during the ongoing high seas biodiversity treaty proceedings at the United Nations and by regional fishing management organizations. This information can help these leaders more effectively pursue shared goals for maximizing equity, food security, and sustainability on the high seas in the near future. These patterns also help to clearly identify which states may stand to win or lose from alterations to the current order of high seas biodiversity management and highlight how the hegemonic powers in high seas fishing can constructively assume more responsibility in leading toward this improved future. Observations of the apparent dominance of wealthy foreign nations in the EEZs of less-wealthy nations can similarly empower and inspire both citizens and leaders in these regions to have more constructive discussion about best pathways toward securing sustainable and equitable futures for their domestic fisheries. These data also provide an improved understanding of the scope for potential competition between foreign industrial fleets flagged to wealthy nations and domestic small-scale fisheries—competition that is known to create numerous challenges for affected small-scale fisheries and the stakeholder communities linked to these fisheries (*6*, *7*, *42*). The extent and lopsided nature of the dominance of higher-income flag states in industrial fishing can and should also inform ongoing conversations about how fisheries subsidies reform can potentially curb socioecological abuses associated with distant water fishing (*25*). Addressing all of these issues is a time-sensitive matter. Significant stresses are likely to be placed very soon upon the food future and political stability of many of the marine regions where we highlight greatest levels of imbalance in regimes of industrial fishing (*3*–*5*). Success in meeting these challenges on the high seas and within EEZs will matter both for the future of fisheries and the many stakeholders whose economic bottom lines, nutrition, and well-being depend on sustained long-term use of these resources.

MATERIALS AND METHODS

AIS-based characterization of fishing effort

To increase the transparency surrounding control over global fisheries and the benefits that can be derived from fishery resource sharing agreements, we used a big data approach to undertake a global fishery-independent assessment of industrial fishing effort by vessels flagged to higher- and lower-income countries. Use of AIS is required by the IMO for all passenger vessels, all cargo ships greater than 500 gross tonnage, and all vessels greater than 300 gross tonnage engaged in an international voyage. Many fishing vessels are, however, below the IMO's 300 gross tonnage size threshold, and adoption (and enforcement) of these regulations into national legislation varies, with some nations modifying the regulations to be more or less strict as to the size of vessels required to carry AIS (*9*). AIS receivers aboard a vessel transmit information about the vessel's current speed, position, and course along with other vessel identification information (for example, vessel name, MMSI number).

Satellite and terrestrial processed AIS data from January 2015 to December 2016 were provided by Global Fishing Watch (www.globalfishingwatch.org). The Global Fishing Watch data set makes use of convolutional neural networks to identify fishing effort in this global data repository (*10*, *43*). To identify fishing vessels, a convolutional neural network model was trained on tracks of 45,000 marine fishing vessels that had been identified through registries as fishing vessels or nonfishing vessels. Using AIS tracks that have been labeled by experts as fishing or nonfishing for 500 vessels, another convolutional neural network model was trained to identify when a specific AIS point was most likely fishing.

Here, we summarize only the data for industrial fishing, defined here as all fishing effort from vessels >24 m in length [lengths of vessels were compiled from registry records and when not available, estimated by the convolutional neural network, as described in Kroodsma *et al.* (*10*)]. Although no absolute threshold exists for what defines an industrial fishing vessel with respect to length, by including only vessels >24 m in length, most artisanal fishing vessels will be excluded (*11*). By conservatively focusing on vessels >24 m in length, we also confine this analysis to industrial fishing vessels for which AIS coverage is strong. A total of 30,469 vessels >24 m in length were active during the study period and included in the analysis. To examine how the selection of this vessel size threshold affected the analysis, an additional 29,988 vessels that were between 12 and 24 m in length were also included in a separate analysis to examine patterns of fishing effort for vessels >12 m in length for 2016. We used comparisons between AIS and VMS data from Indonesia to create corrections to adjust for any potential underreporting bias in AIS-only analyses of fishing effort in lower-income countries (all methods and results reported in Supplementary Materials). We do not differentiate in any of these analyses between different gear types of industrial fishing. The time between each consecutive AIS point labeled as fishing was calculated and included in the data set as fishing hours. All analyses in this report consider industrial fishing effort that can be detected using AIS and aggregated by fishing hours, referred to throughout as "fishing effort." As an alternative measure of fishing effort, fishing days for each vessel were also calculated, where each fishing day is defined as any calendar day a vessel was determined to be engaged in fishing behavior. We contribute these algorithm-based identifications of fishing effort purely for research purposes and make no legal claims, expressed or implied, about the reported patterns.

The MMSI assigned to each vessel was used to identify unique vessels. Each MMSI number was assumed to correspond to one vessel throughout the study period. The flag state for each vessel was determined using the registered flag state in vessel registries when available, alternatively by the first three digits of the MMSI (the marine identification digits, which correspond to a particular flag state), and finally by a manual review of vessels whose marine identification digits did not correspond to a flag state. Because of a lack of data tracking vessel ownership, vessels that may have had a flag of convenience or were otherwise registered to a flag state other than the vessel owner's state were not identified and were considered part of the fleet of whatever state to which they were flagged. Further description of the methods used for processing the AIS data to determine fishing vessels and fishing effort can be found in Kroodsma *et al.* (*10*).

World Bank country classification and status of fishing entities

All unique vessels were assigned to one of four World Bank income group country categories: high income, upper middle income, lower middle income, or low income (www.worldbank.org; using 2016 classifications). Throughout, we refer to "higher-income nations" to collectively indicate nations classed as either high income or upper middle income. Likewise, we refer to "lower-income" nations when collectively indicating nations classed as lower middle income or low income. We adopt here World Bank practices of using the term "country" (interchangeably with nation and state) to refer to a statistically relevant economic data reporting entity, without any implication of political independence. The proportion of industrial fishing effort attributed to nations from different income categories was compared at the global level, and analyses were then subdivided between the high seas, EEZs, and ocean basins. Fishing effort observed on the high seas and each EEZ was aggregated by the flag state of vessels involved in fishing activity. EEZs without a designated World Bank income classification (high/upper middle/lower middle/low) were excluded from the analysis. The EEZs of state territories were not included because fishing agreements and policies vary widely between territory entities and their sovereign state (table S6). Any fishing vessel whose MMSI marine identification digits indicated that it was flagged to a territory was listed as an unclassified entity in this analysis. When a vessel's flag state was the same as the EEZ it was fishing in, it was classified as domestic fishing. When the MMSI marine identification digits of a vessel did not correspond to a specific flag state or the MMSI number was incompletely reported, the vessel was classified as invalid identity. Ocean basin delineations were based on those of the International Hydrographic Organization; fishing activity that took place outside of these ocean basins (that is, the Red Sea) was not included when comparing fishing activity by ocean basin. The boundaries for both oceanic basins and EEZs were obtained from www.marineregions.org, a project of the Flanders Marine Institute. Mapping of higher- and lower-income fishing effort in Fig. 2 used an equal area 0.5° grid, following past estimates of fishing effort (*1*, *10*).

Comparison of AIS-derived measures of fishing effort to catch reconstruction data

We compared estimations of AIS-derived industrial fishing effort for 2016 generated using the methods described above against reconstructed catch estimates for global marine fisheries generated by the Sea Around Us from 2014 (the most recent year available) (*1*) for all EEZs of countries categorized as high income or low income by the World Bank (upper and lower middle income classifications were not included). More recent data were available and were used for the high seas reconstructed catch estimates, found and described in Sala *et al.* (*25*). For the catch reconstruction estimates, catch is defined as metric tons fished per fishing entity using only industrial fishing catch (this includes both estimated landings and discards). Fishing effort for the AIS data is defined as total fishing hours for each entity. The top five fishing entities for each country's EEZ according to the catch reconstructions and AIS fishing effort data were identified. These top five fishing entities of both lists were compared to assess the rank order consistency of the top fishing entities on the high seas and in each EEZ.

As with AIS data and associated analyses, data on catch reconstructions come with their own set of advantages and challenges (*44*, *45*). While effort and catch are very different measures, they are fundamentally related and often positively correlated (*46*). Consequently, any alignment observed in these comparisons between patterns of AIS-measured effort data and catch reconstruction data provides a potentially valuable first opportunity to validate the efficacy of the AIS fishing effort measures we report and a means to begin building hypotheses that explain congruities and incongruities in pattern match.

SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at http://advances.sciencemag.org/cgi/content/full/4/8/eaau2161/DC1

Supplementary Materials and Methods

Fig. S1. Distribution of 2015 industrial fishing effort by vessels flagged to nations from different income classes as measured using AIS data and convolutional neural network models.

Fig. S2. Distribution of 2016 industrial fishing effort (measured in fishing days) by vessels flagged to nations from different income classes as measured using AIS data and convolutional neural network models.

Fig. S3. Distribution of 2016 industrial fishing effort from vessels flagged to higher- and lower-income nations by high seas ocean basin derived via AIS.

Fig. S4. Geographic distribution of industrial fishing effort from vessels flagged to higher- and lower-income nations for 2016 derived via the AIS in all countries' EEZ.

Fig. S5. Number of vessels for each World Bank income group in FAO registry compared to number of vessels detected through AIS in Global Fishing Watch's vessel database for vessels >24 m in length.

Fig. S6. Distribution of 2016 industrial fishing effort (measured in fishing hours) by vessels flagged to nations from different income classes as measured using AIS data and convolutional neural network models for vessels >12 m in length.

Fig. S7. Distribution of 2016 industrial fishing effort (measured in fishing hours) by vessels flagged to nations from different income classes using both AIS data and Indonesian VMS data for vessels >24 m.

Fig. S8. Distribution of 2016 industrial fishing effort (measured in fishing hours) by vessels flagged to nations from different income classes using AIS data, Indonesian VMS data, and corrected low-income and lower middle–income fishing effort for vessels >24 m.

Table S1. Comparison of top 5 fishing flag states for the high seas, and all high- and low-income EEZs based on AIS-derived effort (total fish hours per fishing state) in 2016 and reconstructed catch (total metric ton caught per fishing state) in 2014 (most recent year of available data).

Table S2. Top 20 most active fishing flag states on the high seas in 2016.

Table S3. Top 20 most active fishing states across all EEZs for the year 2016 based on AIS-derived estimates of industrial fishing effort.

Table S4. Top 20 most active fishing states across all lower-income (lower middle income and low income) EEZs for the year 2016 based on AIS-derived estimates of industrial fishing effort.

Table S5. Breakdown of countries that have variably codified IMO ratified standards for use of the AIS.

Table S6. List of countries and other entities used in the analysis and their World Bank income group country classifications (2016).

Table S7. Amount of fishing effort by Indonesian vessels >24 m from Indonesian VMS data.

Table S8. Number of vessels >24 m in the FAO registry and detected via AIS for each lower-income country.

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Acknowledgments

Funding: This work was supported by Benioff Ocean Initiative (to D.J.M., C.J., and F.H.J.), Alfred P. Sloan Foundation (FR-2015-65479) (to D.J.M.), the SESYNC (National Socio-Environmental Synthesis Center) National Science Foundation (DBI-1052875) (to D.J.M., C.D.G., and E.H.A.), the Wellcome Trust Our Planet, Our Health (grant no. 106864MA) (to C.D.G. and E.H.A), and the National Geographic Society's Pristine Seas project and E. Sala (to J.M.). **Author contributions:** Conceptualization: D.J.M., C.J., and F.H.J. Data analysis and interpretation: D.J.M., C.J., D.K., and J.M. Writing: D.J.M., C.J., F.H.J., C.D.G., and E.H.A. with input and feedback by all the other authors. **Competing interests:** The authors declare that they have no competing interests. **Data and materials availability:** All data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials. Rasters of daily fishing effort, gridded at 0.1° by flag state, are available at globalfishingwatch.io, as are the results of the neural net vessel classification algorithm. Additional data related to this paper may be requested from the authors.

Submitted 18 May 2018
Accepted 9 July 2018
Published 1 August 2018
10.1126/sciadv.aau2161

Citation: D. J. McCauley, C. Jablonicky, E. H. Allison, C. D. Golden, F. H. Joyce, J. Mayorga, D. Kroodsma, Wealthy countries dominate industrial fishing. *Sci. Adv.* **4**, eaau2161 (2018).