TECHNICAL REPORT: A PRACTICAL APPROACH OR ESTIMATING MARINE FISHERIES ASSET VALUE

The Changing Wealth of Nations 2021

Managing Assets for the Future

WORLD BANK GROUP

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A Practical Approach or Estimating Marine Fisheries Asset Value

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1. Introduction

Aquatic resources, including marine fish stocks, represent an important component of natural capital in coastal nations, especially small-island developing states. Approximately one in ten people rely on fisheries and aquaculture for their livelihoods (FAO 2016). Despite their global importance, fisheries are measured and assessed on the basis of data that are frequently incomplete, limited, or even inaccurate. This impedes countries from effectively evaluating the importance of the sector as a path for sustainable development and hinders effective management of this important natural resource. Accounting for fish and other aquatic resources has lagged behind the accounting effort of other natural capital assets such as forests and subsoil assets. The System of Environmental Economic Accounting (SEEA) (United Nations et al. 2014) provides the framework for accounts, and fisheries accounting is further elaborated in SEEA for Agriculture (FAO and United Nations 2016) and SEEA for Fisheries (FAO 2006). But so far lack of data has held back national environmental accounting efforts for fisheries.

This report starts with a broad overview of the challenges to constructing global fisheries asset accounts, and the data sources used. Subsequent sections document data and methodology in much greater detail. Section 2 describes the data and methods to estimate annual resource rent: catch data, landed value and price data, fishing costs, and fishing subsidies. Section 3 describes the approach to assessing stock status required for simple estimates of asset value. The potential impacts of climate change on fisheries asset value are discussed in the last three sections: future ocean conditions (Section 4), spatially-explicit population dynamic modeling (section 5), and future economic value under climate change (section 6).

The Changing Wealth of Nations 2018 defined a roadmap for including marine fisheries in the global wealth database, but data were not available for fully integrating these accounts until now. Assets are included in CWON when the necessary data are: (a) available for a large number of countries (at least 100), (b) updated regularly to provide a time series, and (c) publicly available. The value of an asset is generally defined as the discounted value of benefits the asset will generate over its lifetime. Benefits in the case of natural capital like fisheries are defined as the resource rent, the value of the stock itself, net of all costs of harvesting. As a renewable resource, the asset lifetime and stream of rents from fisheries are potentially infinite, if fisheries are managed sustainably, within the bounds of natural regeneration. If, on the other hand, fisheries are overexploited and harvested beyond natural regeneration, then the catch and resource rent will decline over time, as is the case for minerals, a non-renewable resource.

Approach to fisheries asset valuation

Fisheries asset valuation has two distinct parts with specific data requirements:

Step 1. Estimating current annual resource rent for a given year: resource rent is a key concept both to wealth accounting and more broadly to fisheries management. It represents the value that the asset—in this case, fish stocks—contributes to fishing revenue. The revenue generated by fishing must cover all the costs—fuel, vessel costs (a "reasonable" return on fixed capital invested in fishing), labor, and all other costs. Any revenue above payments needed for fishing inputs is considered rent attributable to the fisheries assets themselves. Where rent is positive, the value of fisheries is positive; where landed value does not fully cover costs, rent is negative and the value of fisheries is zero. Because of the widespread use of subsidies in fishing operations, it is useful to distinguish rent under current management (private rent with subsidies) and the broader economic or social rent would be if subsidies were not included in the calculation

This step requires information about catch volume (by species), fishing cost, landed value and price, and subsidies for each country.

Step 2. Projecting resource tent into the future: Since the value of a fishery depends on the expected rents generated over the lifetime of the fishery, the next step requires estimating the ability of the fishery to continue generating catch (stock status and catch), the future price and costs of fishing, which are also affected both by both management and external effects like climate change. Stock status can provide an indicator of the fisheries' biophysical sustainability. A fishery might generate positive rents, but be managed unsustainably, resulting in a limited time horizon for generating rents, much like exhaustible mineral resources. The potentially devastating impacts of climate change (warming ocean temperatures, acidification) should also be taken into account. Although sustainably managed fisheries have a potentially infinite lifetime (from the human perspective), the lifetime for valuation of renewable assets like fisheries is capped at 100 years in CWON 2021, in keeping with practice by other countries. Finally, this step requires a discount rate to estimate the value of future benefits as with all other assets in CWON, a discount rate of 4 percent is used. These data are required for a time series, 1995 to 2018, and as many coastal countries as possible, 110 out of the 146 countries included in CWON 2021.

Overview of data sources and methods

To assess the fisheries asset value, we gathered information about marine fisheries production (i.e., catch data), the ex-vessel price of each exploited species, fishing cost and fisheries subsidies of each country for the period 1991 to 2018. The catch data for marine exploited species of each country are available from the Food and Agriculture Organisation of the United Nations (FAO) website. FAO provides a comprehensive database on marine fisheries by species, country and year; however, the landed value data of each country is still not publicly available at the FAO website. Also, the catch data from the small-scale fisheries such as subsistence and recreational fisheries are not included in the official reported data to the FAO. To fill this gap we extracted the data from the *Sea Around Us* (SAU) catch reconstruction database which utilizes data from various sources including published literature, informal reports and expert knowledge to derive estimates for all fisheries components missing from the officially reported data. SAU provides catch time series by flag state, fishing sector, species, and catch type starting from 1950 and also links the data to other fisheries-related information for every maritime country including the ex-vessel price data developed by the Fisheries Economic Research Unit (FERU) of the University of British Columbia, cost of fishing and the government subsidies. These data allow us to estimate the landed value, private resource rent (profit) and economic resource rent of fishing in each country.

This report further assesses the fisheries management status of each country by using the percentage of the number of fish stocks in each exploitation status, which is determined by the catch statistic data of each fish stock (see section 3 for details). Climate change is expected to impact fisheries and the future marine fisheries production, hence, the fisheries asset value. The Earth System Model (ESM), the Dynamic Bioclimate Envelope Model (DBEM) and an economic model were combined to explore how the change in marine conditions would potentially impact fisheries asset values under two different climate change scenarios (SSP1-2.6 and SSP5-8.5).

2. Estimating Annual Resource Rent: Catch, Price, Fishing costs, Subsidies

2.1 Catch data

We obtained catch data from two different sources including Food and Agriculture Organisation of the United Nations (FAO) and the *Sea Around Us* (SAU) reconstruction database (www.seaaroundus.org). Marine capture production data (tonnes) of each country and species from 1991 to 2018 were obtained from the latest version of FishStatJ (2020) of the FAO's Fisheries and Aquaculture statistics[1].

Since the reconstructed catch data provided by the SAU database utilized a wide variety of data sources and information to estimate all of the fisheries components such as subsistence catch, recreational catch and discards that are missing from the official reported data (Pauly and Zeller, 2016), we included this set of data in our analysis to provide a more comprehensive estimation of the total asset values of marine fisheries. Annual catch data were extracted from the *Sea Around Us* database of reconstructed catches, which cover the years 1991 to 2016, distributed onto 180,000, 30' latitude x 30' longitude spatial cells of the world ocean (Watson et al., 2004; Zeller et al., 2016). The catch allocation process by the SAU produced spatial time series of landings data from 1991 to 2016 that were aggregated into different fishing entities, and which distinguished between landings by different taxa, different fishing gear types, between distant-water and domestic fleets, different catch types (landings and discards) and between different fishing sectors (including industrial, subsistence, artisanal and recreational). There are 203 fishing entities being included in this study (Supplementary Table S1) and 31 countries are excluded from this analysis (Supplementary Table S2) as these are small island

[1] FAO's Fisheries and Aquaculture statistics (http://www.fao.org/fishery/statistics/software/fishstatj/en).

countries and have not been included in the World Bank list of economies for the Changing Wealth of Nations 2021. There are 2,741 taxa at different taxon levels (species, genus, family, order, class and ISSCAAP levels) included in the database and in this study. Each of the taxon is associated with a functional group which plays a specific functional role in the ecosystem, and there are 31 functional groups in the databases (Supplementary Table S3). Hence, the catch data is also arranged by each functional group.

The catch reported to FAO from its members countries is lower than the reconstructed catch (FAO, 2016). The small-scale fishery sectors, i.e. artisanal, subsistence and recreational received little attention in data collection systems, so their catches are underrepresented in, or absent from, official catch statistics, as are discards and illegally caught fish (Pauly, 2006; Zeller et al., 2015) . Thus, the total SAU reconstructed catch from 1991 to 2016 was around 1.5 – 1.8 times of the total reported catch in Europe and East Asia, which is comparable to the ratio of global reconstructed to the reported catch (i.e. about 1.5 times). The "catch reconstruction" approach utilized a wide variety of data and information sources to estimate the catch of those sectors that are missing from the official reported data. Globally, the reconstructed catch tends to decrease in the recent decade but FAO reported catch remain more or less constant in this decade (Figure 1). In the East Asia and Pacific region, the reported catch still tends to be stable in the recent 10 years, but this is mainly due to the over-reporting by a few countries like China (FAO, 2020).

Since the last allocation of data (through 2016), there has not been another update on the spatial landings data to include more recent global landings from FAO. Therefore, we extended the catch series for the present study based on FAO catches in 2017 and 2018. This was first performed (*i*) by comparing the complete list of fishing countries in the *Sea Around Us* catch database with a list of all countries occurring in the FAO data in 2017 and 2018. Then, (*ii*) we calculated the proportions of catch of each fishing country in the *Sea Around Us* catch database to that reported by FAO in 2016. Finally, (*iii*) we used these proportions and the FAO production data in 2017 and 2018 to estimate the reconstructed catch of each fishing country in these two years, assuming that these proportions did not change much since 2016. The results are catch by each fishing country in 2017 and 2018.

The annual catch in each World Bank region in the period from 1991 to 2018 is shown in Figure 1. The total average annual catch of all fishing entities from 1991 to 2018 is shown in Figure 2. Countries in the East Asia and Pacific region have the highest annual catch in the recent three decades (i.e., 47 million t average annual catch). Countries in Europe and Central Asia have the second-highest catch with an average annual catch of 25 million tonnes over the last 30 years.

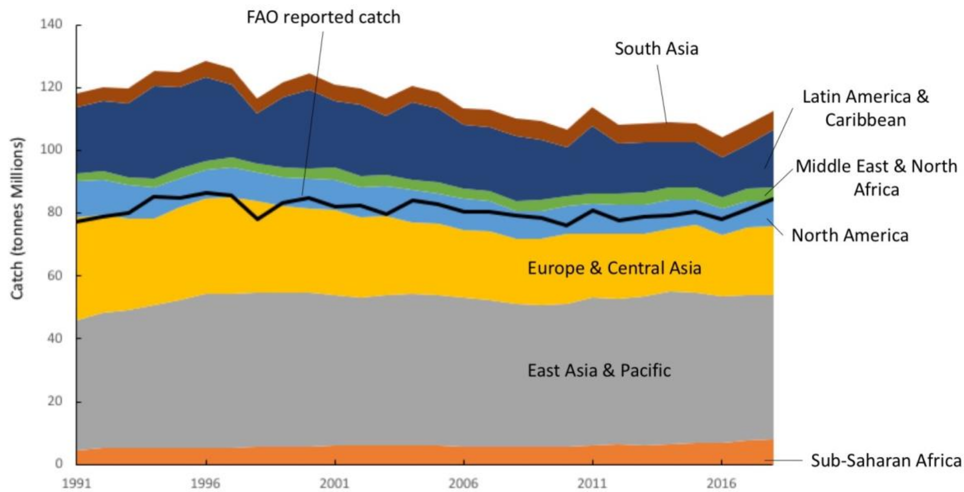


Figure 1. The trend of reconstructed catch (tonnes x millions) in different regions from 1991 to 2018 and the black line represents the FAO global annual reported catch.
Source: Authors' calculations based on data described in the text.

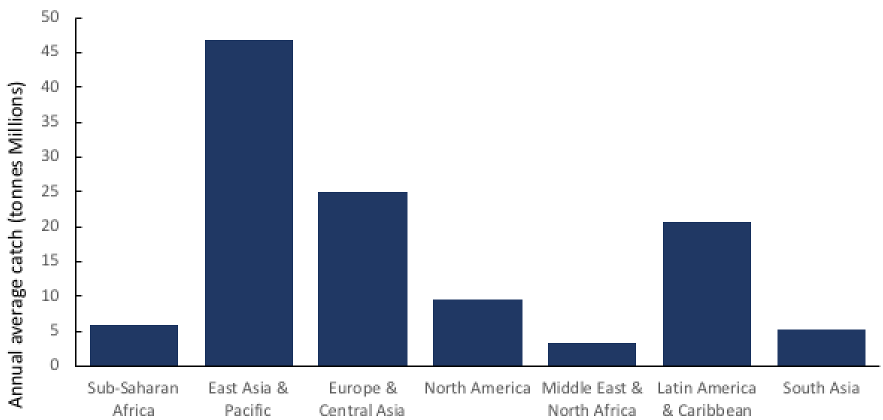


Figure 2. Annual average catch in each World Bank region from 1991 to 2018.
Source: Authors' calculations based on data described in the text.

Using SAU estimates, Industrial fishing dominates fish catch, and artisanal catch is also significant; subsistence and recreational catch are much smaller, but significant for local communities (Figure 3).

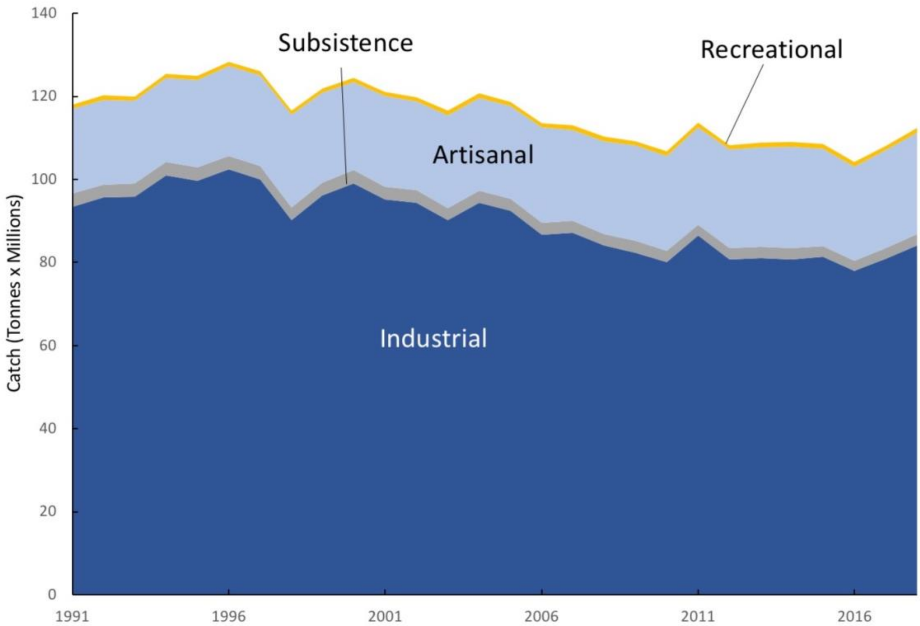


Figure 3. The trend of reconstructed catch (tonnes x millions) in different fishing sectors from 1991 to 2018.

Source: Authors' calculations based on data described in the text.

2.2 Price data

Ex-vessel prices are the prices that fishers receive directly for their catch, or the price at which the catch is sold when it first enters the supply chain. Sumaila et al. (2007) first established a global ex-vessel fish price database to understand the economic behavior of the world fisheries and provide critical information for sustainably managing marine resources. The fish price database assembled by SAU's Fisheries Economic Research Unit (FERU) provided the ex-vessel prices in current and constant US dollars for each exploited marine taxon, by each fishing country for each year from 1950 to 2006 and can be matched to each record of the catch data in the SAU catch database (Pauly and Zeller, 2016, Watson *et al.* 2004). The fish price database was constructed by collecting and compiling scattered data from secondary data sources and working with the international partners and developing a rules-based model for gap filling (Swartz et al.

2013, Tai et al. 2017). Hence, the most up-to-date database has fish price data from 1950 to 2010 for marine taxa that are destined for both direct and non-direct human consumption.

Two additional adjustments were made to the price database so that the resulting figures would be consistent with the rest of CWON database:

- Extending the price database from 2010 to 2018: Since the last round of the detailed update of the price data was only up to year 2010, the ex-vessel price data was extended from 2011 to 2018 by assuming constant ex-vessel prices of each taxon by each country from 2010.
- Converting the database to 2018 constant prices: Data on prices are maintained in the SAU database in constant 2010 USD. Price deflators provided by the World Bank that have been used for other asses in CWON 2021 were used to convert the 2010 USD price to 2018 USD.

2.3 Landed values

By combining the catch data with the fishing ex-vessel price data of each marine taxon, the landed values can be estimated for different fishing country at different spatial locations. For example, the total landed values in each grid cell in a particular year is calculated by:

$$LV_{yr} = \sum_{i}^{i=m}(\sum_{j}^{j=n}(C_{i,j,yr} * P_{i,j,yr}))$$

where LV_{yr} is the total landed value in a particular grid cell in a particular year (*yr*), *i* is the fishing country, *m* is the number of countries fishing in this grid cell, *j* is the exploited marine taxon, *n* is the number of marine taxa caught by each fishing country in that grid cell in year *yr*, $C_{i,j,yr}$ is the annual total catch of a taxon (*i*) caught by country *j* in year *yr* and $P_{i,j,yr}$ is the unit ex-vessel price data of this particular taxon (*i*) by fishing country (*j*) in year *yr*.

FAO catch data are used wherever possible, with SAU catch data adding the missing components. The SAU catch data and price are already matched at a very detailed level that distinguishes taxon, fishing country, and other characteristics, but the FAO data are not, so the first step was to estimate the detailed value of FAO catch. Since the landed value data of the marine capture production of each country are not publicly accessible at the FAO statistic database, we linked the average ex-vessel price of each ISSCAAP group, fishing country and year combination from the SAU FERU ex-vessel price database to the FAO marine production data. When there is no matching price from the SAU FERU ex-vessel price database, the average price of each ISSCAAP group in each year to fill the gap.

The latest year of catch that are associated with ex-vessel price data in the FERU ex-vessel price database is 2016. Thus, we assumed the unit ex-vessel price of each ISSCAAP group kept constant in 2016 and used this price data to fill the gaps in 2017 and 2018. The total landed values of the FAO marine capture production in each year was then estimated by multiplying the FAO catch data with the associated ex-associated price from the FERU database of each ISSCAAP group and country combination. The average global annual landed value is USD 184 billions in constant 2018 USD over the period from 1991 to 2016. Countries in high-income group and upper middle-income group have the largest share (~80%) of the global landed value in the recent decade (Figure 4).

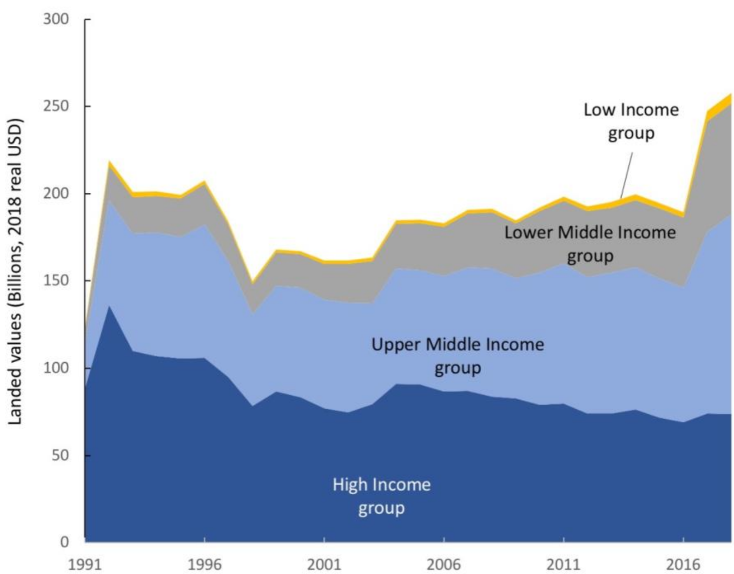


Figure 4. The trend of landed values (billions, 2018 real USD) in different income groups from 1991 to 2018.

Source: Authors' calculations based on data described in the text.

2.4 Fishing cost

The global fishing cost database from Fisheries Economic Research Unit (FERU) (Lam et al. 2011) is arranged by gear type and country, updated to cover the years from 1991 to 2018, and to further distinguish costs of small-scale, large-scale and distant water fleets. Small scale fleet includes all vessels under 12m or 15 GT using static gears (drift and/or fixed netters, vessels using pots and/or traps, vessels using hooks, vessels using passive gears only for vessels). Large scale fleet includes all vessels using towed gears (dredgers, demersal trawlers and/or demersal seiners, vessel using other active gears, vessels using polyvalent active gears only, purse seiners, beam trawlers, pelagic trawlers) and vessels over 12m or 15GT using static gears operating within the EEZ of the flag state. The long-distance fleet includes vessels over 24m or 100GT operating in other countries fishing regions or beyond the EEZ of the flag state. The fishing cost data in this database is arranged by year, fishing entity, super gear type and fishing sectors. Gear types included in the database were based on the gear categorization system of the Sea Around Us project (http://www.seaaroundus.org/) (Table 2). The fishing sectors are segregated into Industrial, subsistence, artisanal and recreational fishing sectors.

Date sources:

We focused on collecting secondary data for vessels operating in major fisheries and in major fishing nations in each of the seven World Bank regions of the world: (1) Sub-Saharan Africa; (2) East Asia and Pacific; (3) Europe and Central Asia; (4) North America; (5) Middle East and North America; (6) Latin America and Caribbean; and (7) South Asia. The first step was to identify the sources of fishing cost data, mainly secondary sources, i.e. websites and grey literature, such as government, FAO, and consultant reports. The detailed sources of the data are in the excel file, "ReferenceList_FishingCost2-2.xlsm".

We have collected 4,300 data points with fishing cost data from various sources. These data are reported for 56 countries across the seven regions (Figure 5).. A large proportion of the observed data are in Europe & Central Asia (~80% of the total data points) because European Unions (EU) compiles comprehensive information of fishing cost data for the fishing fleets of Europe, particularly in the Annual Economic Reports published by the Publications Office of the

European Union. However, the fishing cost data of countries in many other regions are not recorded or are not publicly available.

We collected the data from different fishing gear types (Table 2) and grouped them into 8 super gear type (Table 2). The number of observed data for each of the super gear types are shown in Figure 6. Both small scale gear type and bottom trawl have the largest number of fishing cost data points, 31% and 27% of the total number of observed data points, respectively.

The observed fishing cost data range from 1973 to 2015 and the data are biased towards recent years 2008 to 2015 (Figure 7), with a much smaller number of observations before that.

Our observed data also bias towards the high-income group and the number of data in this group represents about 89% of the total number of observed data (Figure 8). However, fishing cost data in the other three income groups are under-represented.

Table 2. Different fishing gear types and super gear types adopted by the Sea Around Us project.

Super Gear Type	**Fishing Gear**
Bottom trawl	bottom trawl
Bottom trawl	shrimp trawl
Bottom trawl	beam trawl
Bottom trawl	otter trawl
Pelagic trawl	pelagic trawl
Longline	lines
Longline	pole and line
Longline	longline
Longline	hand lines
Purse seine	encircling nets
Purse seine	purse seine
Purse seine	small encircling nets
Gillnets	gillnet
Gillnets	trammel nets
Other	other
Other	pots or traps
Other	other nets
Other	dredge
Other	hand or tools

Other	dragged gear
Other	mixed gear
Small scale	artisanal fishing gear
Small scale	long distance small scale
Small scale	recreational fishing gear
Small scale	subsistence fishing gear
Small scale	cast nets
Small scale	bagnets
Small scale	harpoon
Small scale	hand or tools
Small scale	small scale seine nets
Small scale	small scale encircling nets
Small scale	small scale trammel net
Small scale	small scale gillnets
Small scale	small scale other nets
Small scale	small scale pots or traps
Small scale	small scale lines
Small scale	small scale hand lines
Small scale	small scale pole lines
Small scale	small scale longline
Small scale	small scale purse seine
Unknown	unknown class
Unknown	unknown by source
Unknown	unknown by author

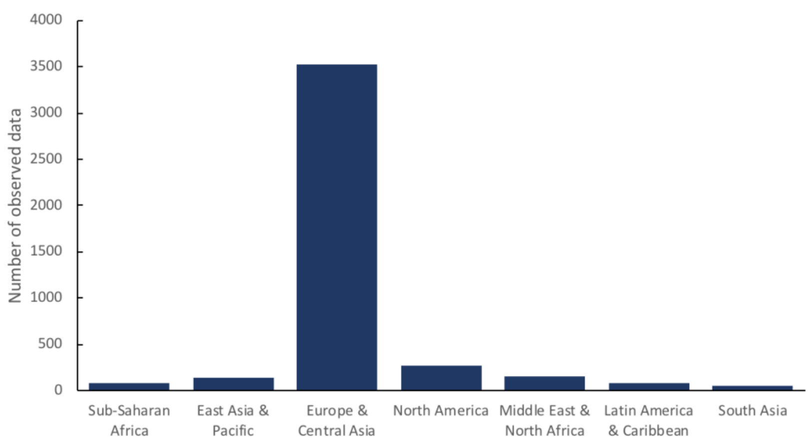


Figure 5. Number of observed fishing cost data points in each World Bank regions.
Source: Authors' calculations

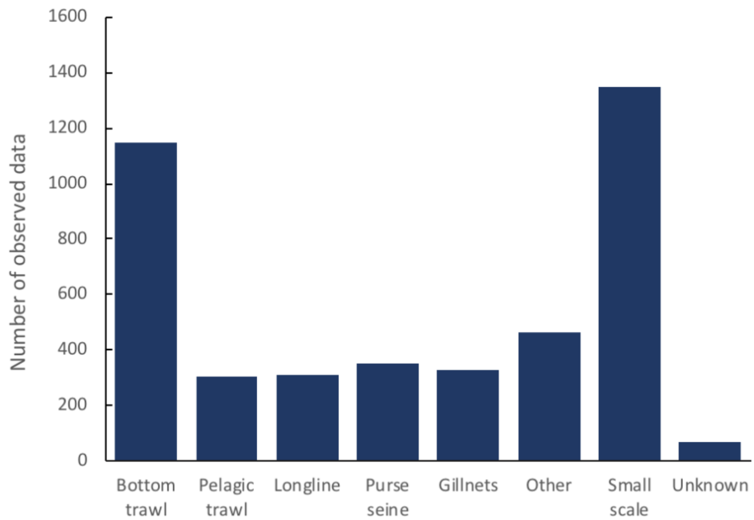


Figure 6. Number of observed fishing cost data points for each super gear type.
Source: Authors' calculations

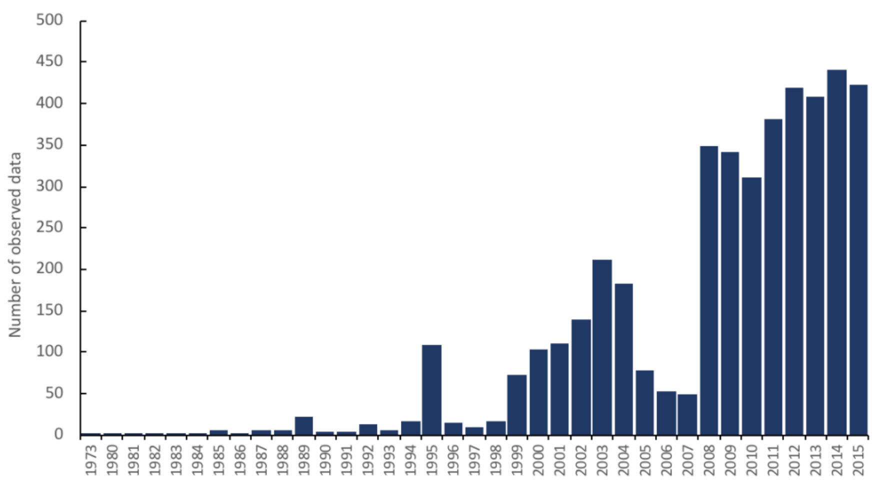


Figure 7. Number of observed fishing cost data points in each year.

Source: Authors' calculations

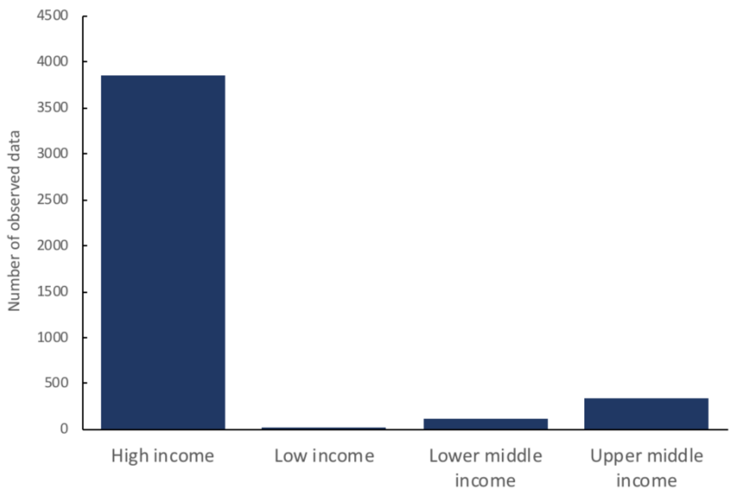


Figure 8. Number of observed fishing cost data in each income group.
Source: Authors' calculations

Updating the fishing cost database

The database was created and updated through three major steps: first, we categorized the different types of fishing costs and designed the structure of the database. Second, we collected cost data ("observed cost") from different sources. Finally, we filled in gaps in the database by interpolation, carry forward and carry backward. Two types of cost, variable (operating) and fixed, were distinguished. Costs associated with operating fishing vessels were categorized as variable costs because they vary with the level of fishing activity. The major items under variable costs include fuel, salaries for crew, repair and maintenance costs of vessels and gear, and other running cost, which includes the cost of selling fish via auction, of fish handling and processing (e.g. the purchase of ice). The other category is the fixed cost, which do not vary with the level of fishing activity and are usually regarded as "sunk" and consist mainly of the amount invested in vessels, i.e. their capital value. However, investment in a vessel does not necessarily represent a "sunk" cost if the vessel can be used in other fisheries or economic pursuits, i.e. implies that they are malleable. Interest and depreciation costs fall into this category. Under the European Union (EU) fisheries data collection framework (DCF), depreciation and interest (whether actual or opportunity costs) are referred to as "capital costs". Interest cost reflects the opportunity cost of capital, and depreciation cost is the replacement cost for normal wear and tear of the fishing vessels. Some more descriptions on the opportunity costs are provided in the Supplementary material.

Data standardization:

Most of the data points report fishing costs in current Local Currency Units (LCU). LCU fishing costs were converted to constant 2018 USD using market exchange rates and deflators applied to all other assets in CWON 2021: World Bank Global Economic Monitor (https://databank.worldbank.org/reports.aspx?source=1179&series=DPANUSLCU#) and the exchange rate for EURO was from IMF (National currency per US dollar, period average) (https://data.imf.org/regular.aspx?key=61545862). We then standardized the unit fishing cost of each cost type by dividing the fishing cost in constant 2018 USD by the catch from the observed data point using this formula:

$$UnitCost_{USD2017} = \frac{Cost_{USD2017}}{Catch}$$

Adjusting for outliers with Winsorization

Given the relatively small number of observations and the wide range of values, the data set was adjusted for outliers. In this study, all outliers were set to a specified percentile of the data using Winsorization. A 95% quantile was used, i.e. all values below or above the 2.5th or 97.5th percentile were set equal to the value corresponding to the 2.5th percentile, and correspondingly for values above the 97.5th percentile. The mean squared error of the Winsorized sample mean was smaller than that of the full sample mean (Searls, 1966; Ernst, 1980; Fuller, 1991).

The process of replacing a specified number of extreme values with a smaller data value has become known as *Winsorization* or as *Winsorizing the data*. This process has its pros and cons:

a. Pros of winsorization:
    i. Classical statistics such as the mean and standard deviation are sensitive to extreme values. The purpose of Winsorization is to "robustify" classical statistics by reducing the impact of extreme observations.

ii. Winsorization is sometimes used in the automated processing of many v variables and large datasets when it is impossible for a human to inspect each and every variable.

iii. Winsorization allows us to identify variables that might contain contaminated data or are long-tailed and require special handling in models.

b. Cons of Winsorization:

i. All of the nice statistical formulas that are used to make inferences (such as standard errors and confidence intervals) are based on the assumption that the data are a random sample that contains all of the observed values, even extreme values. The tails of a distribution are extremely important, and indiscriminately modifying large and small values invalidates many of the statistical analyses that we take for granted.

ii. the fishing cost may be underestimated.

Filling in the fishing cost data gaps

We first got the average fishing cost of each unique combination of super gear type, year and fishing entity from all the observed data and then filled the missing gaps with these observed data of the exact match of year, fishing entity and gear type. A score of 1 was assigned to records with data from secondary sources, i.e. an exact match of country and gear type. We calculated the ratio of the total unit cost to the ex-vessel price data of each data point with observed cost data. To generate a more conservative estimate of fishing cost, the data with cost to price ratio in the top 25% quantile were replaced with the median cost-to-price ratio. The cost-to-price ratio of the countries within the same income groups are assumed to be more similar than those within the same geographic region and we calculated the average cost-to-price ratio of each income group in each year from all the observed data. We then carried backward, carried forward and interpolated the ratio for each income group for the whole time series (1991 to 2018). However, there is no cost-to-price ratio from the observed data for countries in low income groups. So, we assumed the cost to price ratio is equivalent to the average of the cost to price ratios among the three other income groups (i.e., lower middle, high and upper middle-income groups) in each year. The missing gaps were filled with the average fishing cost to price ratio values with matched year and income group. A score of 2 means that the ratio data were assigned from records in the same income group (i.e. matching income group).

Meanwhile, we calculated the proportion of the cost of each cost type (including fuel, labour, maintenance, running, depreciation, opportunity and other fixed cost) to the total cost for each year and income group combination. Then, we assumed the cost proportions of each cost type is similar within the same income group in each year. The average cost proportion of each cost type from the observed data was used to fill the missing gaps in each income group and year. The fishing cost of each cost type was then calculated by multiplying the cost proportion and the total unit cost estimated from the cost to price ratio in the previous step.

Table 3. Table summarized the steps for filling in the missing gaps of the fishing cost database and has the descriptions of the score assigned to each data point. The score implies the quality and certainty of the data point.

Steps	Details	Score
1	Fill the records with observed data in the same year, fishing entity and Super gear	1
2	Fill the records with cost to price ratio in the same year and income group	2

We only consider the fishing cost of non-distant water fleet when computing the total fishing cost. It is difficult to differentiate distant water fleets (DWF) from non-DWF for the catch in the high seas. However, for countries fishing in other countries' EEZ, we can assume that the fishing vessels are DWF. We will use the unit fishing cost of DWF for computing the cost of these fishing fleets in the next stage. However, at this stage, we just use the unit cost of non-DWF for computing the total fishing cost.

Some countries (including Gaza Strip and North Mariana) have no fishing cost data for unknown fishing gear type. We used the regional average of the fishing cost in the regions of these two countries for filling up the gaps.

Fishing cost trends

This section reviews trends in fishing costs by income group and geographic region. Total global fishing cost increased from USD 101.6 billions in 1991 to USD 192 billions in 2018 in constant 2018 USD (Figure 9). Trends in fishing costs largely follow trends in catch. Similar to trends in fish catch, countries in the East Asia and Pacific region have the highest annual total fishing cost accounting for 43% of the total fishing cost from 1991 to 2018. Countries in Europe and Central Asia have the second-highest catch and corresponding fishing costs. Among the different fishing sectors, Industrial fishing has the highest total fishing cost (Figure 10) roughly 74% of the total global fishing costs.

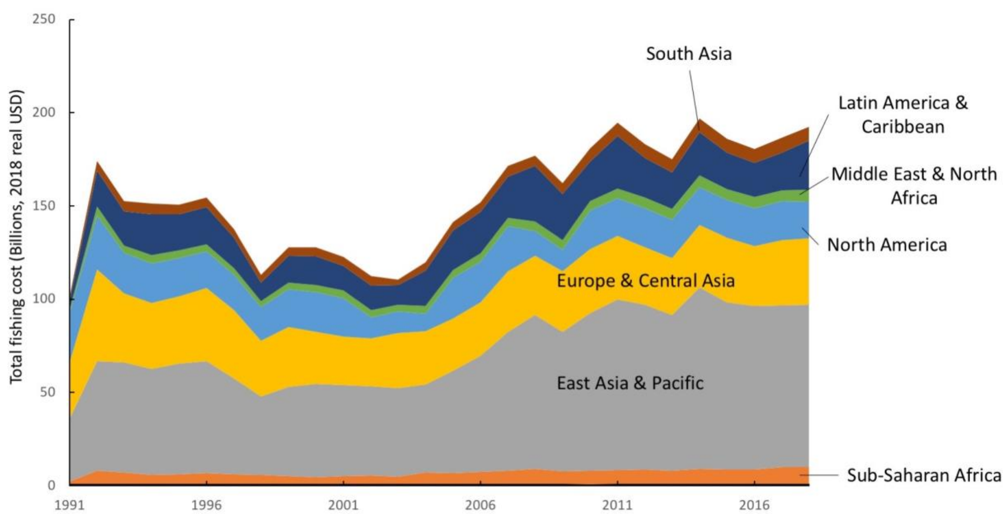


Figure 9. The trend of fishing cost (billions, 2018 real USD) in different regions from 1991 to 2018.

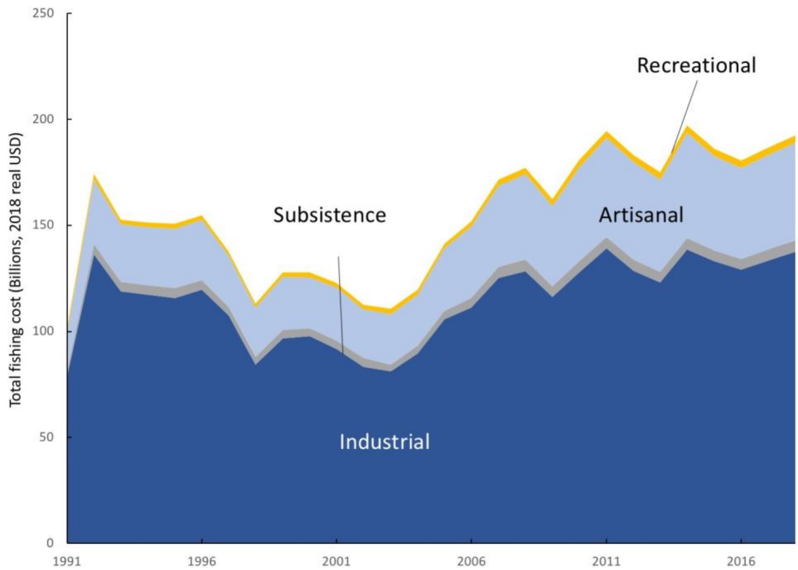


Figure 10 The trend of total fishing cost (USD in 2018 real dollar) in different fishing sectors from 1991 to 2018.

Countries in both high-income group and upper middle-income group have the largest proportion (~80%) of the global total fishing cost among other income groups in the recent decades (Figure 11). The annual total fishing cost of countries in high income group and upper middle income group are USD 77.1 billions and USD 50.5 billions in 2018 real dollar, respectively. Labor cost contributes to the largest proportion of the total fishing cost among other cost types for countries in the high-income group (i.e., 35%) (Figure 12). However, for countries in the other three income groups, fuel cost is the cost that contributes to the largest proportion of the total fishing cost among other cost types (ranges from 25 to 27% in these three income groups).

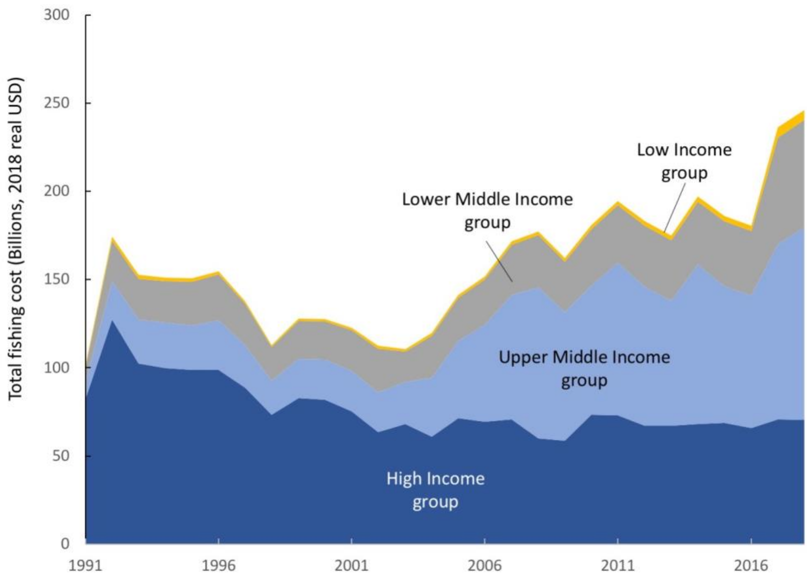


Figure 11. The trend of annual fishing cost (billions, 2018 real USD) in different income groups from 1991 to 2018.

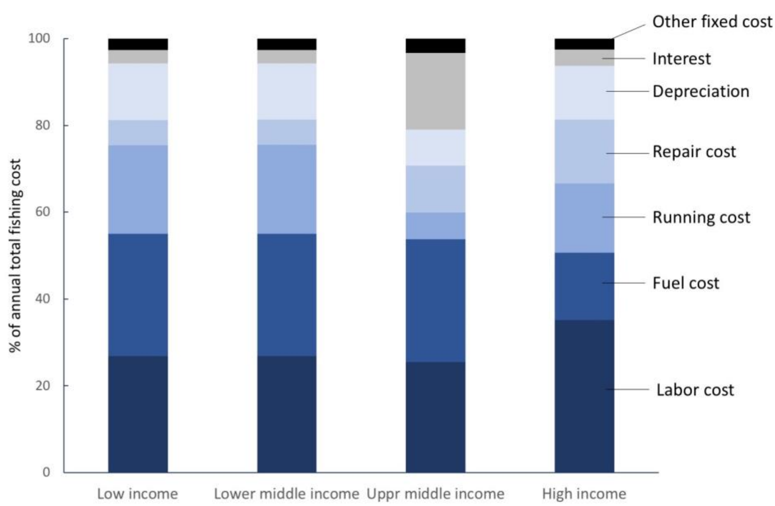


Figure 12. Percentage of annual fishing cost of each fishing cost type in different income groups (1991 to 2018).

Bottom trawl and small-scale fishing gear such as bag nets and artisanal fishing gears (Table 2) are the two gear types that contribute to more than 50% of the total annual fishing cost in the recent decades (Figure 13 and 14). Labor cost contributes to the largest proportion of the annual total fishing cost in all different gear types (range from 41% to 53%) (Figure 13). Fuel cost has the second largest proportion of the annual total fishing cost in all different gear types (range from 25 to 34%).

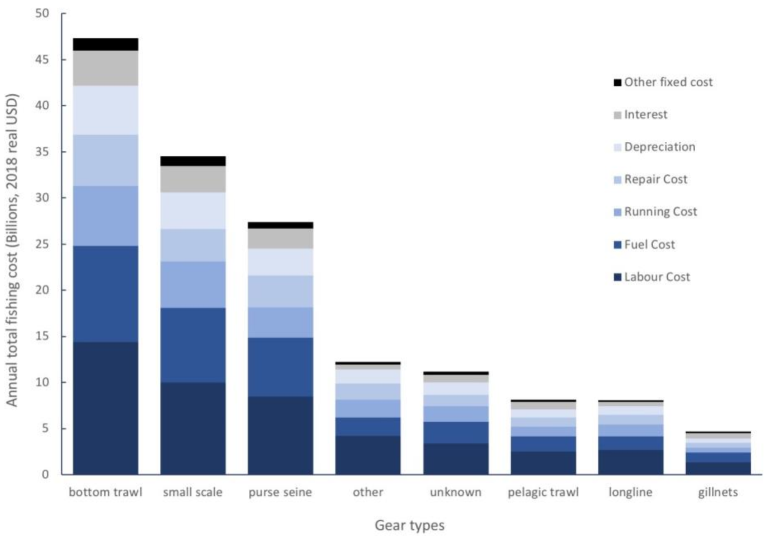


Figure 13 Percentage of annual fishing cost of each fishing cost type in different fishing gear types (1991 to 2018).

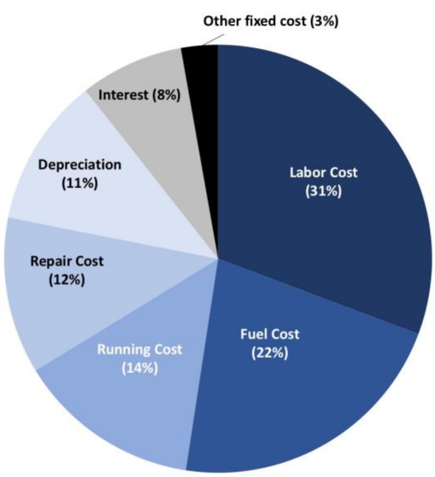


Figure 14 Percentage of fishing cost of each fishing cost type from 1991 to 2018.

2.5 Fishing subsidies

Subsidies can be categorized as capacity-enhancing, beneficial or ambiguous, defined by their effect on fishing practices and stocks (Sumaila et al., 2010). Capacity-enhancing subsidies put further pressure on the marine resources, especially in countries where demand is growing. This category of subsidies enhances overcapacity and overfishing by reducing costs to private operators and increasing private sector profits (Milazzo, 1998).

Beneficial subsidies can be considered as 'investment' programs in fish stocks and include, for example, fisheries research and development. Ambiguous subsidies may benefit or harm fish stocks depending on the local circumstances, for example, fisher assistance packages.

Capacity-enhancing subsidies, accounting for half of the total fisheries subsidies globally, include:

- Tax exemption programs;
- Fuel subsidies;
- Foreign fishing access payments;
- Boat construction renewal and modernization programs;
- Fishing port construction and renovation programs;
- Fishery development projects and support services;
- Marketing support, and storage infrastructure programs.

For the calculation of resource rent, only the direct subsidies to private operators are included: fuel subsidies, foreign fishing access payments and tax exemption programs.

Sources of fishing subsidy data

The original fishing subsidy data are obtained from various sources including Organization for Economic Cooperation and Development (OECD), FAO, Asia-Pacific Economic Cooperation (APEC), published reports and literatures. In the original dataset, we collected the subsidy data of 165 maritime countries with 30 types of subsidies from 1989 to 2019. There are about 4,300 subsidy data points and these data points are biased towards the countries in the high-income group (Table S4) and beneficial subsidies, such as monitoring control and surveillance programs (Table S5). There were only 375 data points for the three subsidies of interest for rent calculations.

Time series subsidy data

The previous versions of the global fishing subsidy table developed by the Fisheries Economic Research Unit, FERU (Sumaila *et al.*, 2010, 2019a, 2019b), standardized the data for one year. Here, we extend the database for 1995 to 2018 by using the steps described below, following the approach described in Sumaila et al. (2019). Four gap filling approaches are applied here depending on the subsidy types and these approaches include a general approach for filling gaps for all subsidy types, except fuel subsidies, fishing access agreements and marine protected areas (MPAs), for which we used customized approaches. Here are the steps for the general approach for filling in the gaps of the global fishing subsidy data:

1. Prepare and clean the dataset

We extracted the landed values of each fishing entity for the catches within and outside its own EEZ (e.g., OwnEEZ = 1 represents landed values within EEZ; OwnEEZ = 2 represents landed values outside EEZs; and OwnEEZ = 3 represents landed values from the high seas). Then, we categorized which subsidy types are related to EEZ catch and which subsidy types are related to the catch from all regions (including its own EEZs, other countries' EEZs and high seas). Subsidy types for fisheries management, research development, and rural fisher development were grouped into the EEZ and subsidy types for boat construction, port construction, fisheries development, marketing infrastructure, buyback programs, fisher assistance programs and tax exemptions were assigned to the catch for the whole fishing fleet group of a country fishing within and outside its own EEZ. We used the latest subsidy dataset (Sumaila *et al.*, 2019a) as a reference to determine which subsidy type in each country where no evidence of subsidy is found.

Since the raw fishing subsidy data are in different currencies, we standardized these data to 2018 USD dollars by using the GDP deflators and the exchange rates in 2018 provided by the World Bank. Then, we calculated the subsidy intensity (SI), which is the ratio of subsidy amount and the total landed values, using the reported catch data for each subsidy type per country.

2. Filling in the gaps

We first fill in the subsidy table with the raw data with the same country, subsidy type and year from the raw fishing subsidy data table. Then, we assumed that subsidy payments are similar between countries within the same income groups (i.e., high income countries (HIC), upper medium income countries (UMIC), lower medium income countries (LMIC) and low-income countries (LIC)). We therefore grouped all the countries into these four income groups, using the classification provided by the World Bank. The subsidy amount provided to the marine capture fisheries sector is assumed to vary depending on the economic status of a country. Hence, in the second step, we calculated the weighted average *SI* value by each subsidy class and income group. The weighted average SI per subsidy class (*j*) for each income group in each year was multiplied with each country's landed value to calculate the missing subsidy amount of the data points that we found evidence of the occurrence of subsidy but lack of quantitative data. For each data point:

$$Subsidy_{i,j,yr} = SI_{j,IG,yr} * LV_{i,j,yr}$$

where $Subsidy_{i,j,yr}$ is the estimated subsidy amount for country *i* and subsidy class *j* in year *yr*, $SI_{j,IG,yr}$ is the weighted average subsidy intensity across all raw subsidy data within the same income group *IG* with subsidy class *j* in year *yr*, and $LV_{i,j,yr}$ is the landed value for country *i* and subsidy class *j* in year *yr*.

For those data points that are still missing subsidy data after the previous step, we used the weighted average $SI_{j,IG}$ with the same subsidy class *j* and income group *IG*. The subsidy amount is then estimated by using this SI with the landed value of each data point. Finally, we fill those remaining data points with missing subsidy amount with zero subsidy. Also, we used the latest subsidy database developed by (Sumaila *et al.*, 2019a) as a reference for the data points of countries and subsidy classes in a particular year that have no evidence of reported subsidy. Here, we assumed that if there is no evidence of subsidy of a particular subsidy class of a country in a year, then there is no evidence of subsidy of this subsidy class of this country in all other years. In each of the step above, we assigned a score to the data to indicate the source and the quality of the data (Table 4).

Table 4 Quality score showing the source and the quality of the subsidy data.

Quality score	Definition
1	Reported data
2	Fill with weighted SI values with the same year, subsidy class and income group
3	Fill with the weighted SI values with the same class and income group
4	Zero subsidy due to no evidence of reported subsidy in the FERU Subsidy database. Apply to all years.

a. Fuel subsidy

We followed the approaches from Sumaila *et al.*(2008) and prepared the data table with fuel amount consumption by each country using the fuel use intensity (FUI), which is the amount of fuel use per tonne of catch (Parker *et al.*, 2018; Greer *et al.*, 2019). In the study by Greer *et al.* (2019), FUI is arranged by region (Table SX) and we linked the FUI to each data point by using region that a country belongs to. The total fuel amount of each country and subsidy class is then estimated by multiplying the FUI with the catch amount:

$$Fuel_{i,j,yr} = FUI_m \ * Catch_{i,j,yr}$$

where $Fuel_{i,j,yr}$ is the fuel consumption of each country *i* and subsidy class *j* in year *yr*, FUI_m is the fuel use intensity of each region, and catch is the total catch of a country *i* in year *yr* associated to subsidy class *j*.

Then, we calculated the subsidy per tonne of fuel used for each data point with raw subsidy data. We first assigned the raw fuel subsidy data to those data points with matching year, country and subsidy class. Then, we calculated the weighted average subsidy per tonne of fuel used for each income group. Missing values are estimated by multiplying each country's fuel consumption in each year to the weighted average subsidy per tonne of fuel used in each income group. We also assigned the quality score to the data point according to the information used (Table 5).

Table 5. Quality score showing the source and the quality of the fuel subsidy data.

Quality score	Definition
1	Reported data
2	Fill the gaps with weighted average fuel use intensity (FUI) by year and income group and then calculate the subsidy by multiply the FUI with the fuel amount and the subsidy per tonne of fuel use of each data point
3	Fill the gaps with weighted average fuel use intensity (FUI) by income group and then calculate the subsidy by multiply the FUI with the fuel amount and the subsidy per tonne of fuel use of each data point
4	Zero subsidy due to no evidence of reported fuel subsidy or no catch data.

b. Foreign fishing access payments

Fishing access fee is the amount of subsidy paid by a country to its fleets to attain the rights of fishing in other countries' EEZs under the fishing access agreement. The landed values of marine species that are caught in other countries' EEZs by each country are extracted from the Sea Around Us catch database. Then, we calculated the SI for the fishing access fee dividing the raw fishing access subsidy by the landed values in other countries' EEZs. The weighted average SI for the fishing access fee was calculated for each income group. Missing fishing access values estimated by assigning the SI values with the same year and income group to the data point and the fishing access subsidy was calculated by multiplying the SI value with the landed value by this country in other EEZs.

A previous study (Belhabib *et al.*, 2015), estimated that an average ratio of compensation paid for accessing to other countries' EEZs (such as West African waters) by EU and China is 6% of the annual average landed values taken by their distant-water fleets from other countries' EEZ. Here, we used this average rate as a proxy for estimating the fishing access subsidy of all the countries with missing fishing access subsidy but have catches in other countries' EEZs. Finally, we assigned a value of zero for all countries that have no evidence of reported fishing access subsidy and/or have no catch in other countries' EEZ. A quality score is attached to each data point (Table 6).

Table 6. Quality score showing the source and the quality of the foreign fishing access subsidy data.

Quality score	Definition
1	Reported data
2	Fill with weighted Access SI values with the same year, class and income group and then calculate the access fee subsidy using this Access SI value and the landed value by this country in other EEZs.
3	Fill with the average Access SI values (6%) to the data point with catch and landed value in other EEZs
4	Zero subsidy due to no evidence of reported subsidy in the Pew Subsidy Data table and/or no landed value in other countries' EEZs. Apply to all years

c. Subsidies on marine protected areas

The total subsidies on marine protected areas (MPAs) of each country equal to the total management cost (MC) of all MPAs in a country and the cost for establishing (EC) the new MPA(s) in each country.

$$TC_{i,yr} = EC_{i,yr} + \sum_{n=1}^{yr} MC_{n,i}$$

where $TE_{i,yr}$ is the total subsidies on MPAs in country i in year yr, $EC_{i,yr}$ is the establishment cost of MPA(s) in country i in year yr and $MC_{n,i}$ is the management cost of all MPAs of country i. The total management cost of all MPAs of a country in a particular year was estimated by summing up the management cost of all MPAs including those established in the first year and those that established in other years and the latest year.

We first obtained the global database of marine protected areas from the United Nations Environment World Conservation Monitoring Centre (UNEP-WCMC) (https://www.protectedplanet.net) which has the information including the size and the year of establishment. Then, we linked these MPAs to all those maritime countries that are included in this study. For those MPAs that are managed by multiple countries, we divided the areas of these MPAs equally by the number of countries which manage them. Based on the study by McCrea-Strub *et al.* (2011), we extracted the per unit area (km^2) cost of establishing and running an MPA of a given country. The per unit costs of running and establishing an MPA vary non-linearly with the MPA size and they are being assigned into 8 size classes. Then, the size of each MPA in each country was assigned to each of these size classes and the total EC and MC of each MPA can be calculated by linking it to the per unit area cost of establishment and managing the MPA. We also assigned the quality score to each of the data point according to the quality of the MPA subsidy data (Table 7).

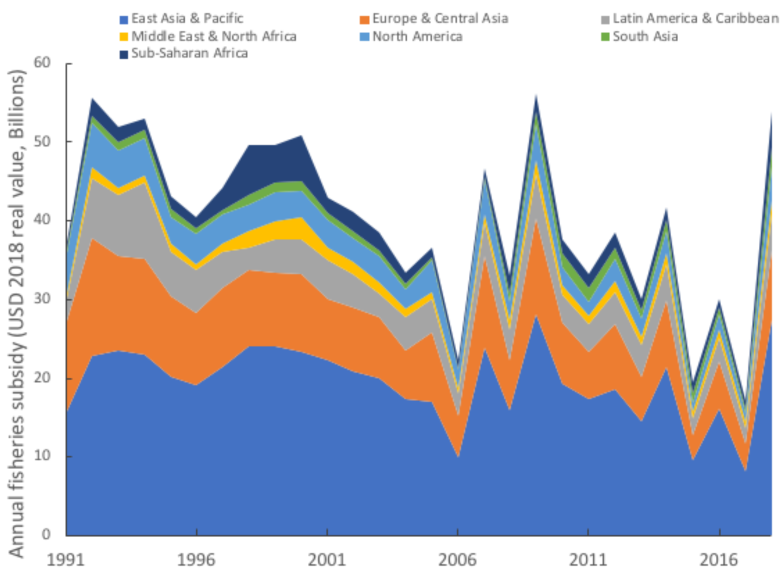
Table 7. Quality score of subsidy data of MPA subtype.

Quality score	Definition
1	Reported data
2	Fill with estimated establishment cost of MPAs established in that year and management cost of all MPAs in each country (TC = EC + MC) from WDPA
4	Zero subsidy due to no evidence of reported subsidy in the latest FERU global subsidy database and/or no MPA data. Apply to all years.

Summary of the subsidy database

The global annual average fishing subsidy is USD 40 billion in 2018 real dollar from 1991 to 2018. Among the seven regions, East Asia and Pacific is the region with the highest amount of fishing subsidy in the period from 1991 to 2018 with an annual average subsidy of USD 19 billion in 2018 real dollar or 48% of the global annual average subsidy (Figure 15a). South Asia is the region with the lowest fishing subsidy amount among all other regions, and this region has an annual average subsidy of USD 1.02 billion in 2018 real dollar (Figure 15a). When we only focus on the three types of capacity-enhancing subsidies including fuel subsidies, tax exemption and foreign fishing access payments, the global annual average fishing subsidy is USD 16 billion in 2018 real dollar (i.e., 40% of the total fishing subsidy) from 1991 to 2018. Among all the regions, East Asia and Pacific is the region with the highest amount of capacity-enhancing fishing subsidy in the period from 1991 to 2018 with an annual average subsidy of USD 9 billion in 2018 real dollar or 48% of the global annual average subsidy (Figure 15b). South Asia is the region with the lowest fishing subsidy amount among all other regions, and this region has an annual average subsidy of USD 0.2 billion in 2018 real dollar (Figure 15b).

(a)



(b)

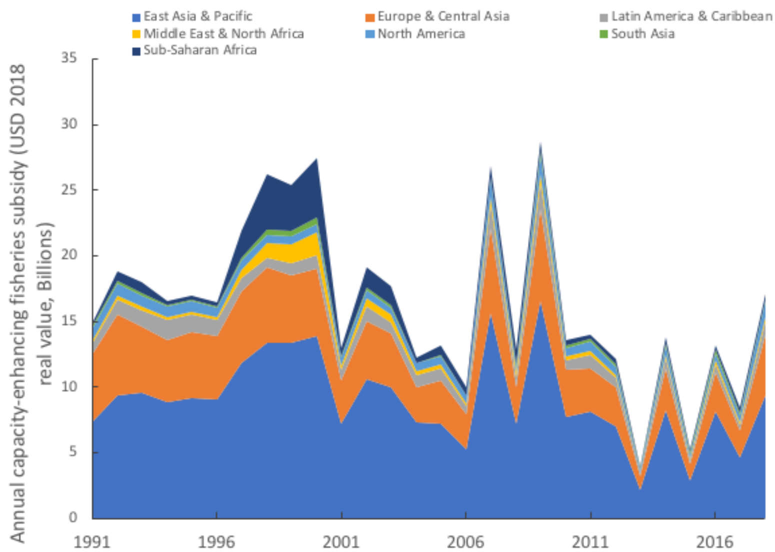
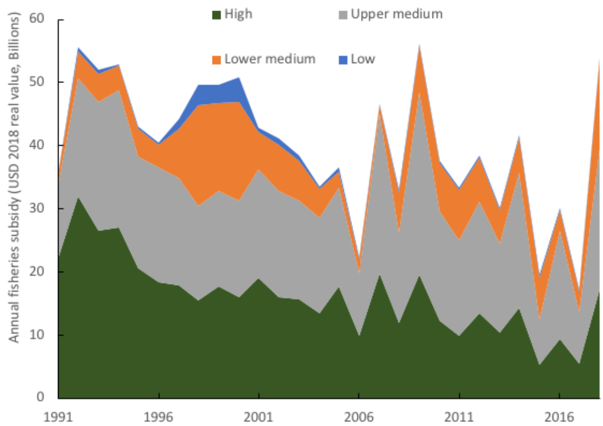


Figure 15 Change in (a) total annual fisheries subsidy (USD in 2018 real dollar) and (b) annual capacity-enhancing subsidies of each region from 1991 to 2018.

Countries in high and upper middle income group have the highest amount of fisheries subsidies among all other income groups with an annual average of USD 16.2 billion and USD 16.8 billion, respectively (Figure 16a). These two countries groups also have the highest amount of capacity-enhancing subsidies among other income groups with an annual average of USD 5.4 billion for high income group and USD 8.3 billion for upper middle income group (Figure 16b).

(a)



(b)

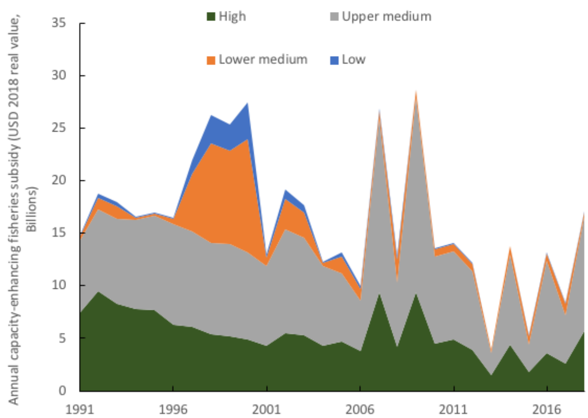


Figure 16. Change in (a) total annual fisheries subsidy (USD in 2018 real dollar) and (b) annual capacity-enhancing subsidies of each income group from 1991 to 2018.

The top 10 countries that have the highest amount of capacity-enhancing fishing subsidy from 1991 to 2018 are China, Thailand, Russian Federation, European Union, Japan, South Korea, United States, Senegal, Malaysia and Peru. The annual average capacity-enhancing fishing subsidy in China is about USD 3 billion in 2018 real dollar (Figure 17) and has a total capacity-enhancing fishing subsidy of USD 85 billion from 1991 to 2018 (Figure 17).

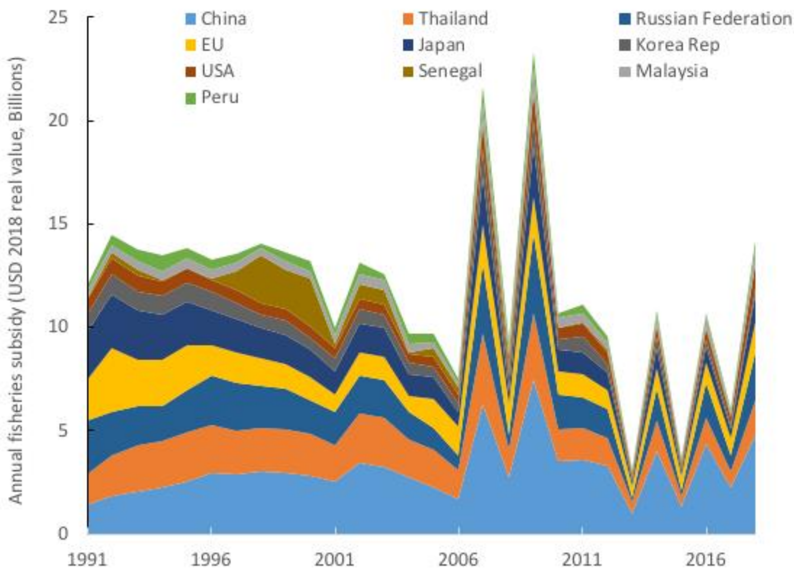
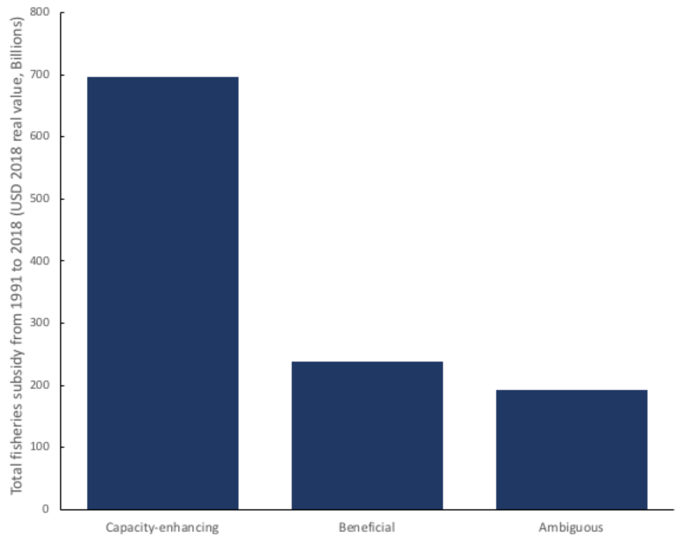


Figure 17 Change in the annual capacity-enhancing subsides of each of the top 10 countries with the highest amount of capacity-enhancing subsidies from 1991 to 2018.

Capacity enhancing subsidies contribute to about more than half (62%) of the total fisheries subsidies from 1991 to 2018 (Figure 18a). The total amount of beneficial and ambiguous subsidies is similar in this period. Amount the capacity enhancing subsidies, fuel subsidies contribute the highest proportion (about 27% of total fisheries subsidies) and then followed by foreign fishing access payments among all of the three subsidy categories (Figure 18b).

(a)



(b)

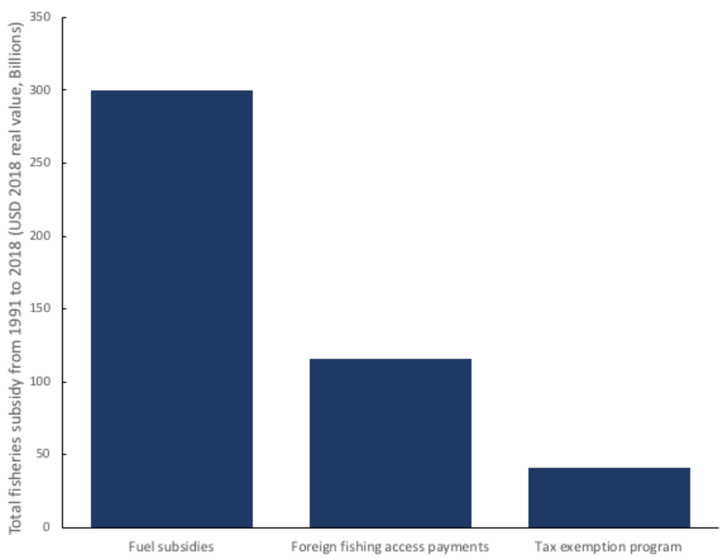


Figure 18 Total fisheries subsidies of (a) different subsidy categories and (b) the three classes of capacity-enhancing subsidies in the period from 1991 to 2018.

Splitting fishing subsidies for small-scale and large-scale fishing sector

A portion of fishing subsidies in some of the fishing nations is allocated to the small-scale fishing (SSF) sector which includes subsistence, artisanal and recreational fisheries. Here, we used the approach in the previous studies (Schuhbauer *et al.*, 2017, 2019; Sumaila *et al.*, 2019a) as the guidelines for splitting the fishing subsidies to SSF from those allocated to large-scale fishing sector of each fishing nation and subsidy class. We first divided the subsidy data to fuel and non-fuel subsidy types. Non-fuel subsidies include 12 subtypes found in one of three categories: 1. Beneficial subsidies: Fisheries management; fisheries research and development and marine protected area. 2. Capacity-enhancing subsidies: Boat construction, renewal and modernization; development programs; port development; infrastructure for market and storage; tax exemptions and fishing access agreements and 3. Ambiguous subsidies: Fisher assistance; vessel buyback and rural fisher community development programs (Khan, 2006; Sumaila *et al.*, 2010, 2016; Schuhbauer *et al.*, 2017).

a. Estimating the SSF non-fuel subsidies

This time-series database is developed based on the SSF subsidy database in 2018 developed by Schuhbauer *et al.* (2019) and the raw SSF subsidy data collected in Schuhbauer *et al.* (2017, 2019). The detailed approach for constructing the SSF subsidy database in 2018 can be referred to Schuhbauer *et al.* (2017, 2019). Before estimating the SSF non-fuel subsidies, we standardized the reported subsidies from their local currencies to 2018 USD by following the methods described in section E(ii) in this report. We first filled the time series database with the proportion of SSF subsidy to total subsidy of the reported data for each fishing entity and subsidy subtype in different years. We used the SSF subsidy proportion here instead of the absolute reported SSF subsidy data because the estimated total subsidy in our time series database may be slightly different from the actual reported total subsidy. We then assigned an SSF data type of "1" which represents these data points with matching reported subsidy data (Table 8).

For the remaining data points that did not have matching reported SSF subsidy data, they were estimated using the proportion of catch data of SSF sector to the total catch data as proxy and the proportion of SSF subsidy to total subsidy in 2018. For each data point, we linked it to the SAU catch data for each fishing sector and then calculated the proportion of SSF catch ($PropSSFCatch_{yr,i}$) to total catch in each particular year (yr) and in 2018 ($PropSSFCatch_{2018,i}$)

for each country (i). An adjustment factor ($Adjustmentfactor_{yr,i}$), which is the same for all subsidy subtypes, was then calculated for each country (i) in each year.

$$Adjustmentfactor_{\ yr,i} = \frac{PropSSFCatch_{yr,i}}{PropSSFCatch_{2018,i}}$$

Then, we calculated the SSF subsidy proportion for each subsidy subtype (x) of each country (i) in 2018 using the SSF subsidy database from Schuhbauer *et al.* (2019).

$$PropSSFSubsidy_{2018,i,x} = \frac{SSFSubsidy_{2018,i,x}}{TotalSubsidy_{2018,i,x}}$$

where $SSFSubsidy_{2018,i,x}$ is the subsidy of subsidy subtype x of country i for SSF and $TotalSubsidy_{2018,i,x}$ is the total subsidy of subsidy subtype x of country i in 2018. Hence, the proportion of SSF subsidy to the total subsidy ($PropEstSSFSub_{yr,i,x}$) of each country (i) in each year (yr) for each subsidy subtype (x) was estimated by the following equation:

$$PropEstSSFSub_{yr,i,x} = Adjustmentfactor_i * PropSSFSubsidy_{2018,i,x}$$

An SSF data type of "2" is assigned to those data points with the proportion of SSF subsidy being filled with this method.

For all rural development subsidies (i.e., subsidy subtype = "C3"), we assumed 100% of this type of subsidies are allocated to small-scale fishers. This is because only rural fisher community of the SSF would benefit from this subsidy based on the description of this subtype. Data points with this subsidy subtype were then assigned with proportion of SSF subsidy = 1 and a data type of "3".

There are circumstances that the proportion of SSF catch in a year specified is greater that in 2018 of a particular country (i.e., $Adjustmentfactor_{yr,i} > 1$) and hence the estimated SSF subsidy proportion by using this adjustment factor may be larger than one. When the SSF subsidy proportion in 2018 has been already high (i.e., >0.9) and the SSF catch proportion in a year specified is even higher , it is justified to assume this subsidy subtype benefits more to the SSF sector and hence 100% of this subsidy is allocated to the SSF. Hence, we assumed the estimated SSF subsidy proportion equals to 1 for those data points with $Adjustmentfactor_{yr,i}$ greater than one and SSF subsidy proportion in 2018 greater than 0.9. However, when the SSF subsidy proportion in 2018 is lower than 0.9 but the $Adjustmentfactor_{yr,i} > 1$, then we assumed the change in the proportion of subsidy versus the change in proportion of SSF catch follows the exponential increasing growth curve. Therefore,

$$PropEstSSFSub_{yr,i,x} = f\left(PropSSFCatch_{yr,i}\right) = a \cdot b^{PropSSFCatch_{yr,i}}$$

where a is value at start and b is the growth factor. These two values were first determined by using two points on the curve (i.e., the point at (1,1) and the point in 2018) for each country. Then, the proportion of SSF subsidy with adjustment factor greater than one and SSF subsidy proportion in 2018 smaller than 0.9 can be estimated.

For data points with foreign access agreement subsidy, we assumed that 0% of this subsidy is allocated to SSF because no SSF fishers and vessels are operated in other country's EEZ. An SSF data type of "6" was assigned to those data points of this subsidy subtype. If there is no reported SSF subsidy of a subsidy subtype of a country specified in 2018, then we also assumed there was no reported subsidy (i.e., $PropEstSSFSub_{yr,i,x} = 0$) in other years of this subsidy subtype and a data type of "7" is assigned to these data points. However, for data points with only SSF catch (i.e., SSF catch proportion = 1) and has subsidy in a particular year but without SSF subsidy in 2018, we assumed all the subsidy goes to SSF in that year (i.e., $PropEstSSFSub_{yr,i,x} = 1$).

If there is no SSF subsidy for a particular subsidy subtype of a country in 2018 but this country has high proportion of SSF catch (>0.8) in a particular year, then we used the proportion of SSF catch in that year as a proxy for estimating the SSF subsidy proportion (i.e., $PropEstSSFSub_{yr,i,x} = PropSSFCatch_{yr,i}$). If the proportion of SSF subsidy of a particular subsidy subtype of a country in 2018 is "NA", we assumed there is no evidence of SSF subsidy for this subsidy subtype of this country ($PropEstSSFSub_{yr,i,x} = 0$). Finally, we assigned a data type of "11" to all the data points which were estimated by model from the last version of the SSF subsidy database in 2018 (Schuhbauer *et al.*, 2019).

Table 8. Data types of the SSF subsidy proportion data.

Data type	Descriptions	Assumption	Reported (R) or Modeled (M)
1	Fill with the reported data for each subsidy subtype and fishing entity in each year (proportion of SSF subsidy) ** using proportion instead of absolute SSF subsidy data because the estimated total subsidy may be different from the actual reported total subsidy.		R
2	Fill with the estimated proportions (adjustment factor * SSFsubsidyProportion_2018 where adjustment factor = SSF catch prop yr / SSF catch prop 2018)		M
3	For all rural development subsidies (C3), 100% is assigned to SSF subsidy	Estimated SSF subsidy proportion =1	M
4	Estimated SSF subsidy proportion > 1 and SSF subsidy proportion in 2018 >0.9 and Class != C3	Estimated SSF subsidy proportion =1	M
5	If estimated SSF Subsidy proportion > 1 and SSF subsidy proportion in 2018 < 0.9, then we assume the proportion of subsidy follows the exponential increasing growth curve (proportion of subsidy vs proportion of catch	The equation is $f(x) = ab^x$. we estimated a and b using two points (1,1) and the point in 2018 for each country.	M
6	Class = B6 (Fishing access)	Estimated SSF subsidy proportion =0	M
7	No Subsidy (2018)	Estimated SSF subsidy proportion =0	M

8	If a country has SSF catch (=1) in a particular year but no SSF subsidy in 2018 and with subsidy in that year, we assumed all subsidy go to SSF in that year	Estimated SSF subsidy proportion = 1	M
9	Use SSF catch prop in that year as a proxy for estimating the SSF subsidies. (>=0.8)	Estimated SSF subsidy proportion = SSF catch prop	M
10	No evidence of SSF Subsidy of this subsidy type (because SSF subsidy in 2018 is NA and datatype is NA)	Estimated SSF subsidy proportion =0	M
11	Modeled from the last round (2018)	Modeled	M

b. Estimating the SSF fuel subsidy

We first filled in the data points with the reported SSF fuel subsidies of matching year and country. For the data points with missing SSF fuel subsidy, we used the proportion of fuel consumption by SSF as a proxy to estimate the proportion of SSF fuel subsidy. The fuel consumption ($FuelCon_{yr,i}$) of each country (i) in each year (yr) was estimated by the fishing effort of the SSF ($FE_{yr,i}$), the fishing hours ($FH_{yr,i}$), the specific fuel consumption rate (SFR) and the fuel coefficient (FC). The equation is:

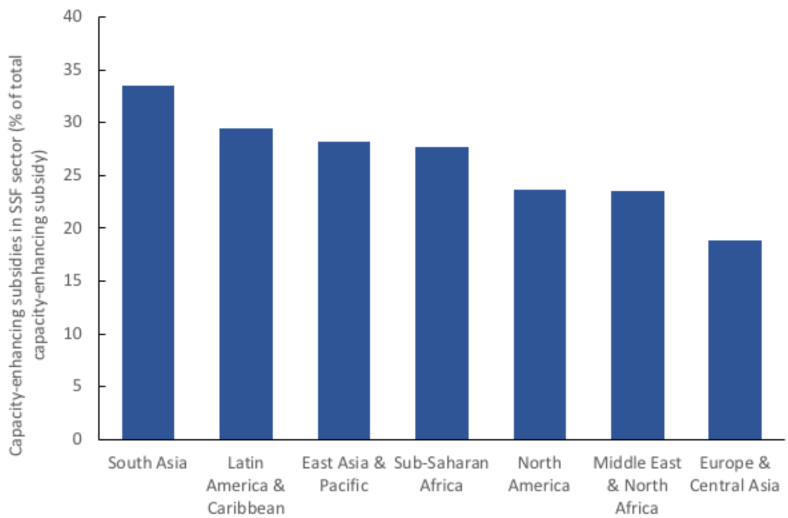
$$FuelCon_{yr,i} = FE_{yr,i} * FH_{yr,i} * SFR_{yr} * FC$$

The fishing effort of SSF of each country in each year was obtained from Greer (2014) and equals to the product of total engine power, number of fishing vessels and the number of fishing days of SSF. SSF vessels are assumed to operate for about 12 hours per day whereas vessels in LSF are assumed to run their engines for 24 hours a day when fishing (Winther, 2007). In (Schuhbauer *et al.*, 2017), the average SFR of small scale fisheries sector is 0.35kg/KW whereas the SFR of large scale fisheries is 0.2kg/KW in the mid 2000s. However, we do not have the estimation of SFR of SSF for other years. So, we used the ratio of 0.35/0.2 as a proxy and the reported SFR of LSF for estimating the SFR of SSF over the whole time period. The average SFR for LSR from 1950 to 2010 is extracted from Greer (2014) and these data were provided by Yanmar (https://www.yanmarmarine.eu). Fuel Coefficient data (FC) is used to account for changes in engine fuel efficiency per year. Here, we used the data extracted from Greer *et al.* (2019) and the year 2000 was set as an anchor point with FC = 1. The fuel subsidy proportion of SSF is therefore estimated by multiplying the proportion of fuel consumption used by SSF to the total fuel subsidy of each country in each year. However, we do not have the fishing effort data and the fuel consumption data of most of the countries in 2017 and 2018, so we carried forward the data from 2016 or earlier years of these countries to fill the data gaps.

Summary of the SSF subsidy database

The annual average total SSF subsidy data of all countries ranges between USD 4.7 to 16.3 billion in 2018 real value from 1991 to 2018. SSF subsidy contributes to about 26% of the total fishing subsidy in this time period. East Asia and Pacific region has the highest amount of SSF subsidy but South Asia has the highest ratio of SSF subsidy to the total subsidy (33.6%) in these 28 years (Figure 19a). For capacity-enhancing subsidies, the annual average total subsidy in small-scale fishing sector of all countries ranges between USD 0.33 to 8.8 billion in 2018 real value from 1991 to 2018. Capacity-enhancing subsidy in SSF contributes to about 24% of the total capacity-enhancing fishing subsidy in this time period. East Asia and Pacific region has the highest amount of SSF subsidy but North America has the highest ratio of capacity-enhancing subsidy in SSF to the total capacity-enhancing subsidy (36.6%) in these 28 years (Figure 19b).

(a)



(b)

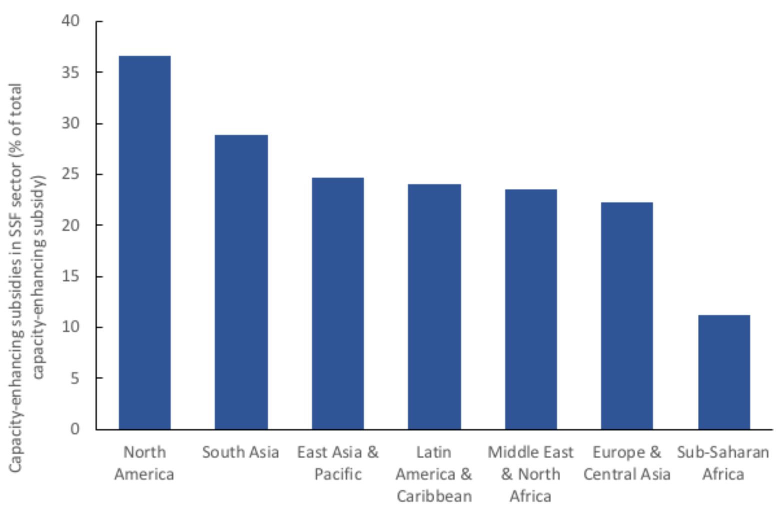
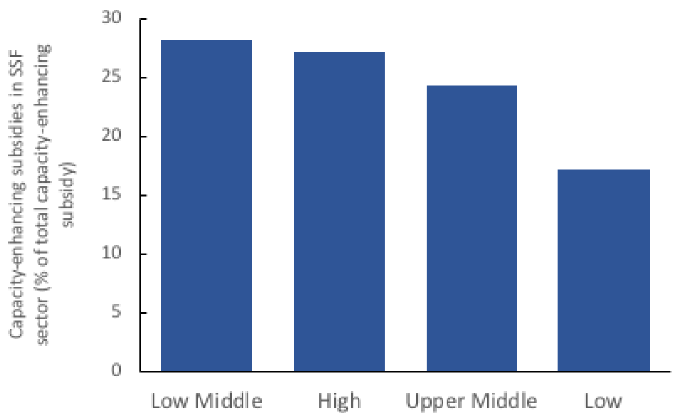


Figure 19. (a) Total SSF subsidies in term of percentage of total subsidies and (b) total capacity-enhancing subsidies in SSF in term of percentage of total capacity-enhancing subsidies in each region from 1991 to 2018.

Among all the country income groups, high-income country group has the highest annual average SSF subsidy (i.e., USD 4.4 billion in 2018 real value) but the lower middle income country group has the highest ratio of total SSF subsidy to total subsidy (28%) (Figure 20a). For capacity-enhancing subsidies, upper middle income group has the highest annual average capacity-enhancing subsidies in SSF (i.e., USD 2 billion in 2018 real value) but the high income country group has the highest ratio of capacity-enhancing subsidy in SSF to the total capacity-enhancing subsidy (31%) (Figure 20b).

(a)



(b)

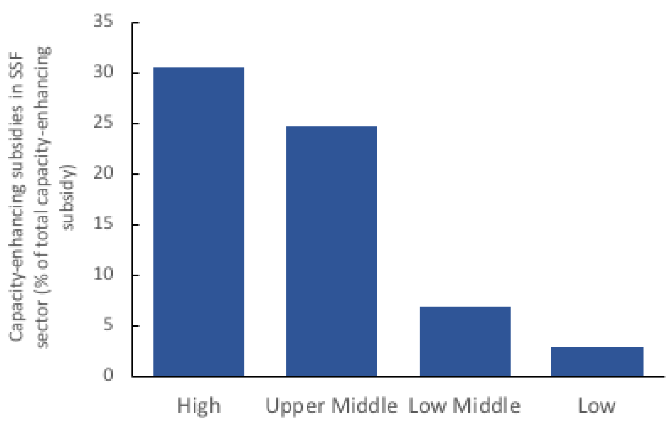


Figure 20. (a) Total SSF subsidies in term of percentage of total subsidies and (b) total capacity-enhancing subsidies in SSF in term of percentage of total capacity-enhancing subsidies in each income group from 1991 to 2018.

Fuel subsidies for SSF has the largest amount (USD 99 billion in 2018 real value) among all the subsidy subtypes. (Figure 21). This subsidy subtype in SSF has the highest percentage of the total fuel subsidies (33%) and then followed by tax exemption program (22%), whereas no subsidy is allocated to SSF for the foreign fishing access payments (Figure 22).

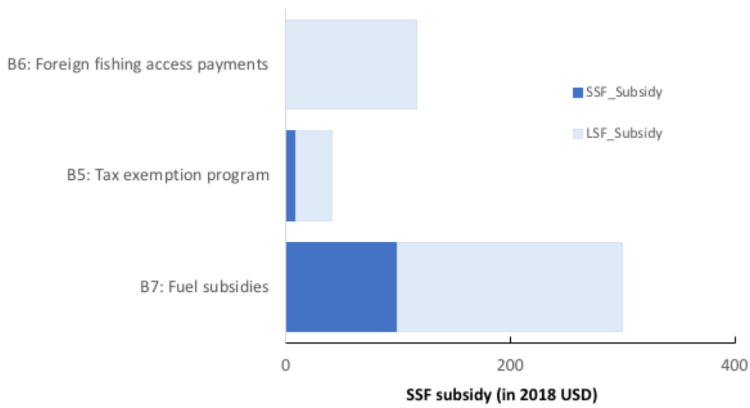


Figure 21. Total SSF and LSF subsidy of each capacity-enhancing subsidy subtype from 1991 to 2018.

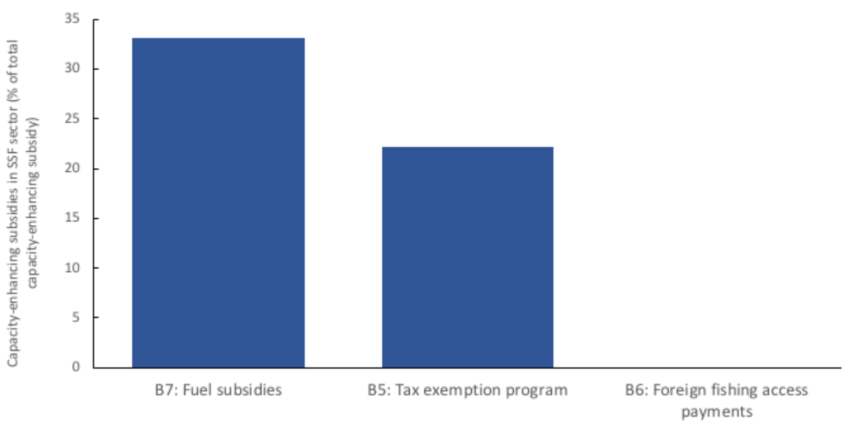


Figure 22. Capacity-enhancing subsidies in SSF in term of percentage of total capacity-enhancing subsidies in each of the three subsidy subtypes from 1991 to 2018.

Our database estimated that the SSF subsidy is the highest in both capacity-enhancing and ambiguous categories and then followed by beneficial category (Figure 23). The percentage of SSF subsidy within each category is quite similar among all these three categories (i.e. 24 to 27%). These results are different from those estimated in Schuhbauer *et al.* (2019) , in which it estimated that the percentage of SSF subsidy ranges from 17 – 27% within each subsidy category. However, the data showed in Schuhbauer *et al.* (2019) only included reported and modeled data in one year (2018) whereas the data in Figure 23 shows the total subsidy data from 1991 to 2018.

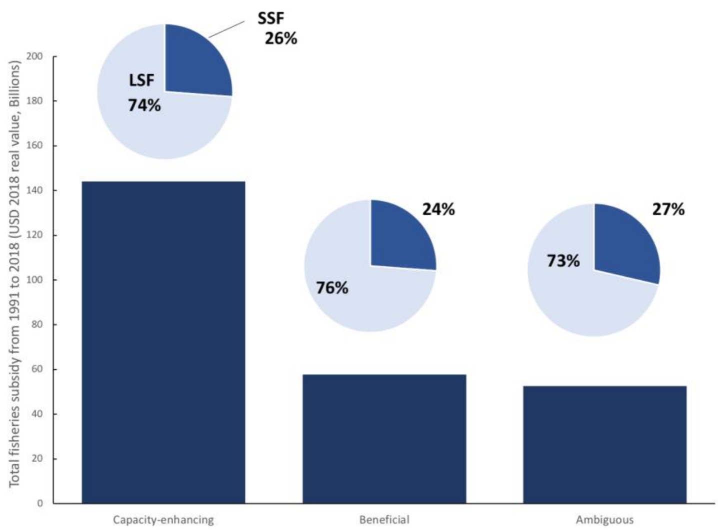


Figure 23. Global SSF subsidy amount grouped by category and the pie charts show the percentages of SSF and LSF subsidies for each category.

3. Assessing the stock and management status of each country

3.1 Methods

Most of the fish stocks are depleted because of overfishing but there are examples that stocks can be rebuilt with effective fisheries management in recent decades (Castilla *et al.*, 2007; Gelcich *et al.*, 2008; Hilborn, 2010; Gallardo Fernández *et al.*, 2011). It is crucial for us to understand the current exploitation status of marine fish stocks in order to assess the effectiveness of the current fisheries management and identify the suitable management strategies in different countries. However, the traditional stock assessment techniques require reliable estimates of stock biomass, which are only available for a small fraction of world's exploited stocks. Only a tiny portion of stocks in developing countries have stock assessments because these countries are usually data poor and lack of stock assessment expertise (Kleisner *et al.*, 2013). Thus, it is not possible for us to have a holistic view on the status of the global fisheries by solely based on the stock assessments which are mostly carried out in developed countries. Here, we used the percentage of the number of fish stocks in each exploitation status to assess the stock status and hence the effectiveness of management measures in each country. This indicator is estimated based on the time-series catch data of each fish stock. The catch data of fish stock in each year can represent different stage of development of a fishery and this indicator can be related to the fishing effort and fish abundance.

As a result of intense exploitation, most fisheries tend to follow predictable stages of development (i.e., rebuilding, developing, fully exploited, overfished, and collapsed). Stock status plots (SSPs) use catch time series to assign individual stocks to different development stages based on catch levels in relation to the maximum or peak catch of the time series (Froese and Kesner-Reyes, 2002; Pauly et al., 2008). The algorithm can be applied to numbers of stocks (species) and to catch tonnage per species to highlight the annual proportions of stocks and total catch in a particular stage. Stocks that are classified as 'overexploited' or 'collapsed' are indicative of a lack of sustainability, especially when the bulk of the catch tonnage is from taxa with these designations.

Here, we defined a stock to be a taxon (i.e., either at species, genus or family level of taxonomic assignment) that occurs in the catch records for at least 5 consecutive years, over a minimum of 10 years' time span, and which has a total catch in an area of at least 1,000 tonnes over the time span analyzed. Then, the number of stocks by status in a particular EEZ in a given year can be estimated and they are presented as percentages. Kleisner and Pauly, (2011) and Kleisner *et al.* (2013) defined the fishing status of different stocks as rebuilding (recovering), developing, exploited, overexploited and collapsed (Table 9).

Table 9. Criteria used to interpret the status of fishery resources based on time series of catch. *Post-maximum minimum (post-max. min.) is the minimum landing after the maximum catch. Sources: www.searoundus.org

Status of fishery	**Criterion applied**
Rebuilding (Recovering)	Year of landing > year of post-max. min.* landing AND post-max. min. landing < 10% of max. landing AND landing is 10-50% of max. landing
Developing	Year of landing < year of max. landing AND landing is < or = 50% of max. landing OR year of max. landing = final year of landing
Exploited	Landing > 50% of max. landing
Over exploited	Year of landing > year of max. landing AND landing is between 10-50% of max. landing
Collapsed	Year of landing > year of max. landing AND landing is < 10% of max. landing

3.2 Summary of the stock status

We used the 3-year running mean of the catch data of each marine exploited species by each country for assessing the stock status. Here, we presented the most frequent status of each marine exploited species of each country in the last 10 years (2005-2014). If we cannot identify the most frequent status in 10 years (e.g., 5 years with overfished and 5 years with recovering), then we used the status of that species in the last year.

The majority of countries (i.e., 128 countries, 68% of the total countries in this analysis) have high percentage (>=50%) of fish stocks in the overexploited and collapsed status in recent decade (Figure 24). This indicates that the stock status is poor and the fisheries management strategies are poorly implemented and not effective in these countries. We also compared the percentage of number of fish stocks in each exploitation status for countries in different income groups (Figure 25). All income groups have high percentage of fish stocks in both overexploited and collapsed status (48% to 59%), and countries in high income groups have the largest percentage of fish stock (59%) that are overexploited and collapsed among others. The percentages of number of stocks in each exploitation status are compared among different regions (Figure 26). North America has the highest percentage of collapsed and overexploited stocks (68%) and then Latin America and Caribbean and Europe and Central Asia are both the second regions with the highest percentage of collapsed and overexploited stocks (62%).

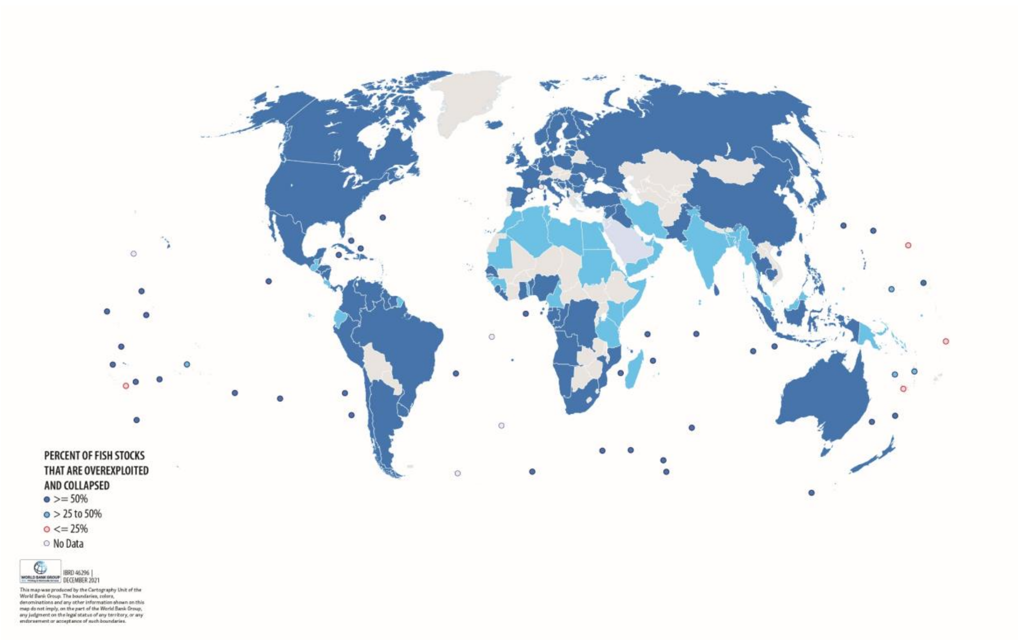


Figure 24 Percentage of number of fish stocks that are overexploited and collapsed in each country.

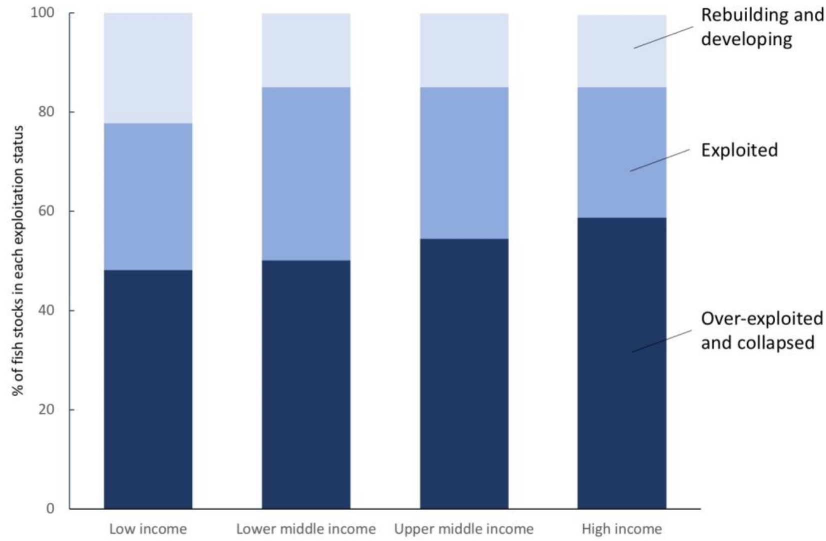


Figure 25. Percentage of the number of stocks in each exploitation status for countries of different income groups.

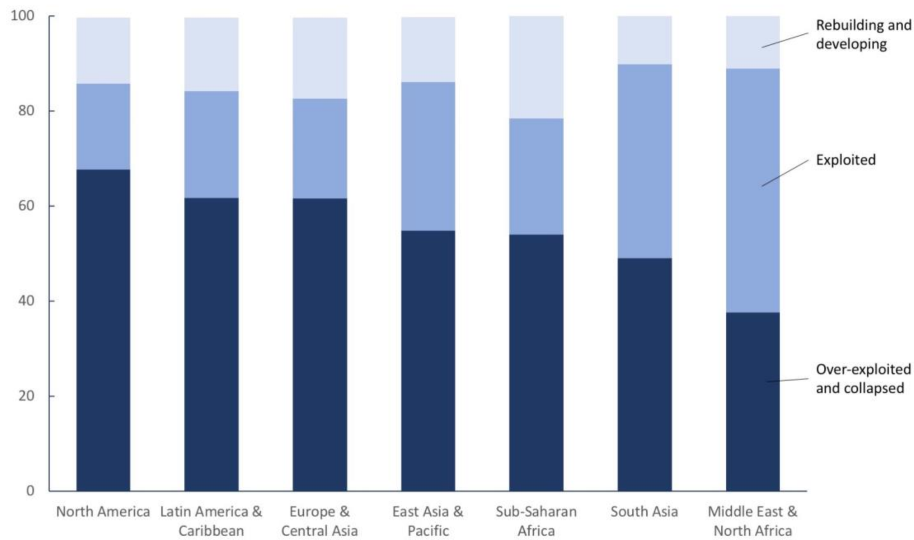


Figure 26. Percentage of the number of stocks in each exploitation status for countries of different regions.

Different fishery exploitation and management scenarios may have different effects on the stock status in different countries. Under some circumstances, the indicators of catch-based stock status may not be able to truly reflect the real status of biomass of the exploited fish stocks. Here, we adapted the scenarios proposed in Kleisner *et al.* (2013) and discussed how each scenario may affect the stock status.

i. *Open-access and regulate fisheries*

Open-access fisheries or without effective management lead to increase in fishing effort and an initial increase in catch but the high fishing pressure will cause the decline in biomass and the catch. This can be reflected in the over-exploited and even the collapsed status. However, there are some confounding factors such as climate shifts which may also cause the biomass and catches to decline and this scenario may also be wrongly interpolated as overfishing and collapsed in the stock status assessment using time-series catch data. When the fisheries regulations are tightened and are effective, we expected the biomass and catches may both increase. However, sometimes it is not the case as strict regulations will result in restriction on harvest and hence reduce the catch. This may not be able to detect by the catch-based SSP.

ii. *Marine protected area*

Marine protected areas (MPAs) covers 2 – 5.7% of the world ocean and the percentage of no-take MPAs is even smaller. However, it is considered as an important tool for conserving biodiversity. In the no-take MPAs, no fisheries are permitted and the level of catch is very low or even zero. In this case, catch-based SSPs may fail to capture the real status of a stock's biomass as it may wrongly classified it as collapsed instead of rebuilding.

iii. *Increase cost of fishing*

Increase in fuel price and/or reduce in the fuel subsidies to the fishing sector leads to increase in fuel cost and hence reduce the fishing pressure. Reduction in the fishing pressure leads to the decline in landings and therefore have a positive effect on the fish biomass. However, the rebuilding of the stocks because of increasing fishing cost cannot be captured by the catch-based stock status assessment.

iv. *Foreign fleets lose permission to fish in EEZ waters*

After the establishment of EEZs, fishing by foreign fleets was controlled through access agreements. Exploitation by foreign fleets usually lead to overexploitation of fish stocks practically for the EEZs of developing countries. For developed countries, since they usually have better monitoring and enforcement, the displacement of foreign fleets in their EEZs may result in a reduction in catches and increase in biomass. However, the fishing pressure from the foreign fleets can be replaced by the domestic fleet quickly. Therefore, the catch based SSP can be misleading in the short term but can truly reflect the exploitation in the long term under this scenario.

v. *Changes in price of fish*

The price of fish changes because of the change in its scarcity, demand and the changing preferences of consumers. When the biomass of a fish is low but the consumers still prefer this fish, the price of this fish may remain high. Fishers may still make an effort to harvest this fish even it has a low abundance. Alternatively, if the consumers do not prefer a particular type of fish and it may lead to decrease in its price, then there is no incentive for the fishers to catch this species even it has a high biomass. Therefore, the catch based SSP may not accurately reflect this scenario.

vi. *Non-target species declines owing to restriction on a target species*

In some circumstances, the by-catch species are landed instead of being discards. For example, the dolphinfish are caught as a secondary by-catch species which is marketed, in the longline swordfish fishery in south-eastern USA waters (Kleisner and Pauly, 2011). When there was a closure of the swordfish fisheries because of overfishing, the landings of swordfish declined as well as the catches of dolphinfish. The catch-based stock status can therefore truly reflect the biomass trend of the target species but not the by-catch species (dolphinfish) as there is no indication that dolphinfish biomass has declined.

Although the use of catch statistics to evaluate stock status have some caveats as indicated above, Duffy (2009) argues that 'no compelling evidence has been suggested that globally average catch data significantly misrepresent trends in global fish abundance'. Also, previous studies has shown that there is strong link between declining catches and declining stock biomass (Froese *et al.*, 2009). So, the catch-based stock status assessment still provides us a straightforward and relatively reliable approach for obtaining a global picture of stock status with limited available data.

PART 2. Projecting the potential impact of climate change on fisheries asset value under different climate change scenarios

4. Projecting future change in ocean conditions

In this section, we projected future changes in physical and biogeochemical conditions in global ocean that are most important for fisheries, such as temperature, salinity, oxygen, acidity, and net primary production. We use the ¼-degree resolution satellite-based sea surface temperature dataset spanning the period from January 1982 to December 2019 (Reynolds et al. 2007; Banzon et al. 2020). To assess future changes, we make use of outputs from two Earth system models, including the Geophysical Fluid Dynamic Laboratory Earth System Model Earth System Model 4 (GFDL-ESM4), the Institut Pierre-Simon Laplace Climate Model (IPSL-CM6-LR), that participated in the Coupled Model Intercomparison Project Phase 6 (CMIP6, Eyring *et al.*, 2016). The ocean component of the CMIP6 Earth system models are relatively coarse with a horizontal resolution of typically about 0.5° to 1°.

The model simulations cover the 1850-2100 period following historical greenhouse gas concentrations from 1850 to 2014, and two future greenhouse gas scenarios from 2015 to 2100. The Shared Socio-economic Pathway 8.5 (SSP5-8.5; Riahi *et al.*, 2017) scenario is a high greenhouse gas emission scenario in which atmospheric greenhouse gas emissions remain unabated over the 21st century reaching a radiative forcing of 8.5 Wm^{-2} by the end of the 21st century. The SSP1-2.6 is a low greenhouse gas emissions high mitigation scenario with a radiative forcing of 2.6 Wm^{-2} in year 2100. One ensemble member for each model is used.

The output of the climate models is remapped onto a 1^ox1^o regular grid. Both physical and biogeochemical conditions change in the upper and the benthic ocean are (i.e., bottom-ocean model layer at each grid point) also fed into the fisheries model applied in the next section. We calculate the projected changes in climatic hazards that are most relevant to the selected marine species in the global ocean. These ocean variables include seawater temperature (surface and bottom), oxygen concentration (surface and bottom), hydrogen ion concentration (a proxy for acidity levels - surface and bottom), net primary production (depth integrated), salinity (surface and bottom) and surface advection.

5. Biological model - Spatially-explicit population dynamic modelling

We employ the Dynamic Bioclimate Envelope Model (DBEM) to project future changes in maximum catch potential (MCP) for exploited marine fishes and invertebrates in different EEZ regions in the world. DBEM is a spatially-explicit population dynamic model that simulates changes in distribution, abundance and potential catches of species on a 0.5° latitude x 0.5°longitude grid of the global ocean. The key components and workings of DBEM are summarized below, while details of the model can be found in Cheung *et al.* (2016):

i. The current distributions of commercially exploited species, representing the average pattern of relative abundance in recent decades (i.e., 1970-2000), are produced using an algorithm developed by the *Sea Around Us* (see www.seaaroundus.org). The algorithm predicts the relative abundance of a species on a 0.5° latitude x 0.5° longitude grid based on the species' depth range, latitudinal range, known Food and Agriculture Organization statistical areas, and polygons encompassing their known occurrence regions. The distributions are further refined by assigning habitat preferences to each species, such as affinity to shelf (inner, outer), estuaries, and coral reef habitats (see www.seaaroundus.org).
ii. An index of habitat suitability (HIS) for each species in each spatial cell based on temperature (bottom and surface temperature for demersal and pelagic species, respectively), bathymetry, specific habitats , salinity and sea ice with 30-year averages of outputs from 1971-2000 from Earth system models (the coarser global models, see 2.1.1). DBEM estimates the temperature preference profile (TPP) of each species by overlaying estimated species distributions with annual seawater temperature and calculated from the area-corrected distribution of relative abundance across temperature for each year from 1971 to 2000, subsequently averaging annual temperature preference profiles (TPP). The estimated TPP is used to predict the thermal physiological performance of a species (aerobic scope) in each area.
iii. Population carrying capacity in each spatial cell is a function of the unfished biomass of the population, habitat suitability (as defined by HSI), and net primary production.

We assume that the average of the top-10 annual catches was roughly equal to the maximum sustainable yield of the species.

iv. DBEM calculates a characteristic weight representing the average mass of the population in a cell. The model then simulates how changes in temperature and oxygen would affect growth and body size of individuals using a sub-model derived from a generalized von Bertalanffy growth function.

v. The model simulates changes in relative abundance and biomass of a species based on changes in population carrying capacity, intrinsic population growth, and the advection-diffusion of adults and larvae in the population driven by ocean conditions projected from the Earth system models. Movement and dispersal of adults and larvae are modelled through advection-diffusion-reaction equations for larvae and adult stages. Larval movement is partly determined by species' predicted pelagic larval duration. Population growth is represented by a logistic function.

vi. Maximum catch potential from each population is predicted by applying a fishing mortality rate at the level required to achieve maximum sustainable yield.

For each simulation, changes in total annual maximum catch potential by near future (2030: 2021-2040), mid-century (2050: 2041-2060) and the end of the century (2100: 2081-2100) relative to current status (1991-2016) under SSP1-2.6 and SSP5-8.5 is calculated for each EEZ and the high sea. Then, we estimated the change in MCP of each species caught by each fishing country. The ensemble average across maximum catch potential projections from the two Earth system models and the projected MCP of each fishing country are estimated in this analysis. We summarized the projected MCP and change in MCP relative to the current status for the countries in each income group in Table 10.

Globally, the projected MCP decreased by 9.3% in the 2100s relative to the current status under the high GHG emission scenario (SSP5-8.5). Among different income groups, countries in the low and lower middle-income group are the countries with the average highest negative impact of climate change on the fisheries production in the long term with a drop of 12.1% and 17.5% of MCP, respectively, from the current status under high GHG emission scenarios. It implies that the fisheries of these countries have higher vulnerability to climate change relative to those in other income groups. When comparing the two scenarios, the high GHG emission scenario has a more negative impact on the fisheries production than the low GHG emission scenario for each income group and globally at the end of this century (i.e., -9.3 % and -1.4% decrease in global MCP from the current status) (Table 10).

Table 10. Projected Maximum Catch Potential (MCP) and change in MCP relative to the current status (%) under two different scenarios in the near future (2030s), mid-century (2050s) and the end of this century (2100s) of different income groups.

Income groups	**Current catch (million tonnes)**	**MCP under SSP1-2.6 (million tonnes) / % of change in MCP relative to current status (in bracket)**			**MCP under SSP5-8.5 (million tonnes) / / % of change in MCP relative to current status (in bracket)**		
		2030s	**2050s**	**2100s**	**2030s**	**2050s**	**2100s**
Low income	1.92	1.98 (3.2)	1.97 (2.7)	1.97 (2.9)	1.94 (1.1)	1.90 (-0.7)	1.69 (-12.1)
Lower middle income	24	22 (-4.9)	22 (-9.0)	22 (-8.4)	23 (-2.1)	22 (-6.6)	20 (-17.5)
Upper middle income	53	53 (-1.2)	52 (-2.2)	53 (-1.2)	53 (-0.5)	52 (-2.1)	48 (-9.8)
High income	43	43 (0.4)	43 (0.6)	44 (2.3)	43 (0.3)	44 (2.1)	42 (-3.6)
Others	0.75	0.69 (-7.7)	0.64 (-14.2)	0.63 (-14.9)	0.69 (-6.9)	0.59 (-20.6)	0.40 (-46.5)
Grand Total	123	121 (-1.3)	120 (-2.5)	121 (-1.4)	122 (-0.5)	121 (-1.5)	111 (-9.3)

We also summarized the projected MCP and change in MCP relative to the current status for the countries in each region in Table 11. Among different regions, climate change has the highest negative impact on the fisheries production in countries in Middle East and North Africa and Sub-Sahara Africa in the long term with a drop of 18.8% and 15.2% of MCP, respectively, from the current status under high GHG emission scenarios. It implies that the fisheries of these regions are more vulnerable to the impact of climate change relative to those in other regions.

Table 11. Projected Maximum Catch Potential (MCP) and change in MCP relative to the current status (%) under two different scenarios in the near future (2030s), mid-century (2050s) and the end of this century (2100s) of different regions.

Regions	**Current catch (million tonnes)**	**MCP under SSP1-2.6 (million tonnes) / % of change in MCP relative to current status (in bracket)**			**MCP under SSP5-8.5 (million tonnes) / / % of change in MCP relative to current status (in bracket)**		
		2030s	**2050s**	**2100s**	**2030s**	**2050s**	**2100s**
East Asia & Pacific	49	48 (-2.6)	46 (-5.4)	47 (-3.8)	48 (-1.0)	47 (-4.5)	44 (-10.6)
Europe & Central Asia	27	27 (1.9)	28 (3.0)	28 (5.9)	27 (1.5)	28 (5.8)	28 (2.3)
Latin America & Caribbean	21	21 (-1.8)	21 (-1.9)	21 (-2.7)	21 (-1.3)	21 (-2.5)	18 (-14.4)
Middle East & North Africa	3.5	3.4 (-4.5)	3.4 (-4.3)	3.4 (-3.0)	3.4 (-3.4)	3.4 (-3.3)	2.9 (-18.8)
North America	10	10 (0.02)	10 (0.04)	9 (-1.7)	10 (0.1)	9 (-1.4)	8 (-13.9)
South Asia	5.5	5.5 (0.2)	5.4 (-1.3)	5.4 (-1.2)	5.5 (0.4)	5.5 (-0.8)	5.0 (-9.8)
Sub-Saharan Africa	6.1	5.8 (-4.7)	5.6 (-8.4)	5.7 (-6.2)	6.0 (-2.3)	5.8 (-4.9)	5.2 (-15.2)
Others	0.7	0.7 (-7.7)	0.6 (-14.2)	0.6 (-14.9)	0.7 (-6.9)	0.6 (-20.6)	0.4 (-46.5)
Grand Total	123	121 (-1.3)	120 (-2.5)	121 (-1.4)	122 (-0.5)	121 (-1.5)	111 (-9.3)

6. Projecting the change in fisheries economic under climate change

6.1 Projected change in fisheries revenues (landed values)

Total fisheries revenue (*TR*) or landed values is the product of ex-vessel price (*P*) and landing (*L*) in the case of commercial fisheries. Global total fisheries revenue (TR) can be expressed as:

$$TR = \sum_{j=1}^{m}[\sum_{i=1}^{n}(P_{ij} * L_{ij})] \quad (11)$$

where P_{ij} is ex-vessel price and L_{ij} is the current landing (the model MCP) of species *i* caught by each country *j*. The total fisheries revenue of each country *j* was first computed by summing up revenue (i.e., landed values) of *n* species caught from its home EEZ *j*, other EEZs and high seas. The current total revenue was estimated using a 26-year (from 1991 – 2016) average ex-vessel prices of each species in 2018 real dollars by each country and the 20-year average MCP data from the DBEM. Then, the global total fisheries revenue was obtained by summing up the total fisheries revenue of all countries, where the total number of fishing countries is m (m = 198).

Projected total revenue (*TR'*) is the product of ex-vessel price (*P'*) and projected MCP of each species and can be expressed as:

$$TR' = \sum_{j=1}^{m}[\sum_{i=1}^{n}(P'_{ij} \ * \ L'_{ij})] \tag{12}$$

The ex-vessel price of each species *i* in each country *j* (P'_{ij}) was assumed to be constant through time, although fish prices could be influenced by local markets, the global supply of fish, preference of consumers, prices of alternative products on the market and also the abundance of targeted species.

We summarized the projected total fisheries revenues and the change in fisheries revenues of countries in each income group under the two climate change scenarios in Table 12. Globally, the projected fisheries revenues decreased by 8.6% in the 2100s relative to the current status under the high GHG emission scenario (SSP5-8.5). Among different income groups, climate change has the highest negative impact on the fisheries revenues of the countries in the low and lower middle-income group are the countries in the long term with a drop of 11.1% and 13.2% of MCP, respectively, from the current status under high GHG emission scenarios. Similar to the impact of climate change on the fisheries production , the high GHG emission scenario has a more negative impact on the fisheries production than the low GHG emission scenario for each income group and globally at the end of this century (i.e., -8.6 % and -1.6% decrease in global fisheries revenues from the current status) (Table 12).

Table 12. Projected fisheries revenues and change in fisheries revenues relative to the current status (%) under two different scenarios in the near future (2030s), mid-century (2050s) and the end of this century (2100s) of different income groups.

Income groups	**Current landed values (billions, USD)**	**Landed values under SSP1-2.6 (billions, USD) / % of change in landed values relative to current status (in bracket)**			**Landed values under SSP5-8.5 (billions, USD) / % of change in landed values relative to current status (in bracket)**		
		2030s	**2050s**	**2100s**	**2030s**	**2050s**	**2100s**
Low income	2.7	2.7 (2.1)	2.7 (1.3)	2.8 (3.2)	2.7 (0.4)	2.7 (0.2)	2.4 (-11.1)
Lower middle income	29	28 (-5.1)	27 (-9.2)	27 (-8.4)	29 (-1.8)	28 (-5.3)	25 (-13.2)
Upper middle income	70	69 (-1.5)	68 (-2.9)	69 (-1.5)	69 (-0.6)	68 (-2.0)	64 (-7.8)
High income	91	90 (-0.7)	90 (-0.5)	91 (0.6)	90 (-0.5)	90 (-0.6)	85 (-6.9)
Others	1.7	1.6 (-7.2)	1.5 (-13.2)	1.5 (-13.7)	1.6 (-6.6)	1.4 (-19.9)	0.9 (-46.6)
Grand Total	194	191 (-1.7)	189 (-2.7)	191 (-1.6)	193 (-0.8)	191 (-2.0)	178 (-8.6)

Table 13. Projected fisheries revenues and change in fisheries revenues relative to the current status (%) under two different scenarios in the near future (2030s), mid-century (2050s) and the end of this century (2100s) of different regions.

Regions	Current landed values (billions, USD)	Landed values under SSP1-2.6 (billions, USD) / % of change in landed values relative to current status (in bracket)			Landed values under SSP5-8.5 (billions, USD) / % of change in landed values relative to current status (in bracket)		
		2030s	2050s	2100s	2030s	2050s	2100s
East Asia & Pacific	81	79 (-2.3)	77 (-4.8)	79 (-3.0)	80 (-1.1)	78 (-4.1)	73 (-9.9)
Europe & Central Asia	39	39 (0.1)	40 (0.8)	41 (4.0)	39 (0.1)	40 (2.9)	39 (0.01)
Latin America & Caribbean	28	27 (-1.2)	27 (-0.8)	27 (-1.1)	27 (-0.9)	27 (-0.9)	25 (-8.6)
Middle East & North Africa	5.6	5.5 (-1.7)	5.5 (-0.6)	5.6 (0.8)	5.5 (-0.5)	5.6 (0.6)	5.1 (-8.1)
North America	25	24 (-1.8)	24 (-1.8)	23 (-5.4)	24 (-0.7)	24 (-3.8)	21 (-16.1)
South Asia	6.0	6.0 (0.1)	6.0 (-1.1)	6.0 (-0.3)	6.1 (0.6)	6.1 (1.1)	5.9 (-1.4)
Sub-Saharan Africa	8.2	7.8 (-5.0)	7.5 (-8.5)	7.8 (-5.5)	8.1 (-1.7)	8.0 (-3.2)	7.3 (-11.8)
Others	1.7	1.6 (-7.2)	1.5 (-13.2)	1.5 (-13.7)	1.6 (-6.6)	1.4 (-19.9)	0.9 (-46.6)
Grand Total	194	191(-1.7)	189 (-2.7)	191 (-1.6)	193 (-0.8)	191 (-2.0)	178 (-8.6)

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Supplementary material

Location of files

File location: Dropbox folder – Data_ToWB_v5_11Nov20>SAUCatch
Link: **https://www.dropbox.com/sh/zdatxyb3d3wmyw0/AADJ0JloAlvL0n7wetFgNHXLa?dl=0**

Table 1. Summary of all the data files from the FERU and SAU databases.

File name	Variables	Aggregated by	Descriptions
CatchLV_Cost_FEYr.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	Fishing Entity, Year	Catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost by fishing entity in each year (1991 – 2018)
AnnAvgCatchLV_Cost_FE.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	Fishing Entity	Annual average catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost (average over the period 1991 – 2018) of each fishing entity
TotAnnAvgCatchLV_Cost.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	By Year	Total annual average catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost of all fishing entities in each year (1991 to 2018)
RegionAnnCatchLV_Cost_byYr.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	Region, Year	Annual average catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost in each World Bank region by year (1991 to 2018)

InGpAnnCatchLV_Cost_byYr.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	Income Group, Year	Annual average catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost by each income group by year (1991 to 2018)
FishSectorAnnCatchLV_Cost_byYr.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	Fishing Sector, Year	Annual average catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost by each fishing sector by year (1991 to 2018)
FishSectorFEAnnCatchLV_Cost_byYr.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	Fishing Sector, Fishing Entity, Year	Annual average catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost by each fishing sector and fishing entity by year (1991 to 2016)
CatchTypeFEAnnCatchLV_Cost_byYr.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	Catch Type, Fishing Entity, Year	Annual average catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost by each catch type in each fishing entity by year (1991 to 2018)
FunGpFEAnnCatchLV_Cost_byYr.csv	Catch Landed values Variable fishing cost Capital cost Total fishing cost	Functional Group, Fishing Entity, Year	Annual average catch, landed values in 2010 real US dollars, landed values in 2018 US dollars, variable fishing cost, capital cost and total fishing cost by functional group in each fishing entity by year (1991 to 2018)

EconRent_USD2018_analysis_May2020.xlsm	Catch Landed values Variable fishing cost Capital cost Total fishing cost Profit Economic rent	Year, fishing entity	Economic rent and profit of each fishing entity in each year from 1991 to 2018. (Unit: USD 2018 real value) **With the "Fisheries Data Check" sheet for year 2016.**
FillSubsidyFinal_11.csv (Location: Data_ToWB_v3>Subsidies)	Fishing subsidy	Fishing entity, year, subsidy class and category	Annual fishing subsidy by country and year in 2018 real US dollars (1991 to 2018).

Economic rent for each country
File location: https://www.dropbox.com/sh/x7lxbdnczn6d9xm/AAByCsEslEnXTXw3Py8Rt6mva?dl=0

- The files in this folder has the catch, landed value, fishing cost, private rent and economic of each country;
- Each file has the data in one year (1991 to 2018).

Table S1. Fishing entities that are included in this study.

Fishing Entity ID	Name	Code	Region	Region ID	Income group	Income group ID
1	Albania	ALB	Europe & Central Asia	3	Upper middle income	UM
2	Algeria	DZA	Middle East & North Africa	5	Upper middle income	UM
3	American Samoa	ASM	East Asia & Pacific	2	Upper middle income	UM
4	Angola	AGO	Sub-Saharan Africa	1	Lower middle income	LM
5	Antigua and Barbuda	ATG	Latin America & Caribbean	6	High income	H

6	Argentina	ARG	Latin America & Caribbean	6	Upper middle income	H
7	Australia	AUS	East Asia & Pacific	2	High income	H
8	Bahamas, The	BHS	Latin America & Caribbean	6	High income	H
9	Bahrain	BHR	Middle East & North Africa	5	High income	H
10	Bangladesh	BGD	South Asia	7	Lower middle income	LM
11	Barbados	BRB	Latin America & Caribbean	6	High income	H
12	Belgium	BEL	Europe & Central Asia	3	High income	H
13	Bermuda (UK)	BMU	North America	4	High income	H
14	Bosnia and Herzegovina	BIH	Europe & Central Asia	3	Upper middle income	UM
15	Brazil	BRA	Latin America & Caribbean	6	Upper middle income	UM
16	Belize	BLZ	Latin America & Caribbean	6	Upper middle income	UM
17	British Indian Ocean Terr. (UK)	IOT	South Asia	7	High income	H
18	Solomon Islands	SLB	East Asia & Pacific	2	Lower middle income	LM
19	British Virgin Islands (UK)	VGB	Latin America & Caribbean	6	High income	H
20	Brunei Darussalam	BRN	East Asia & Pacific	2	High income	H
21	Bulgaria	BGR	Europe & Central Asia	3	Upper middle income	UM
22	Myanmar	MMR	East Asia & Pacific	2	Lower middle income	LM
23	Eritrea	ERI	Sub-Saharan Africa	1	Low income	L
24	Cambodia	KHM	East Asia & Pacific	2	Lower middle income	LM

25	Cameroon	CMR	Sub-Saharan Africa	1	Lower middle income	LM
26	Canada	CAN	North America	4	High income	H
27	Cabo Verde	CPV	Sub-Saharan Africa	1	Lower middle income	LM
28	Cayman Islands (UK)	CYM	Latin America & Caribbean	6	High income	H
29	Sri Lanka	LKA	South Asia	7	Upper middle income	UM
30	Chile	CHL	Latin America & Caribbean	6	High income	H
31	China	CHN	East Asia & Pacific	2	Upper middle income	UM
32	Taiwan, China	TWN	East Asia & Pacific	2	High income	H
33	Christmas Isl. (Australia)	CXR	East Asia & Pacific	2	High income	H
34	Cocos (Keeling) Isl. (Australia)	CCK	East Asia & Pacific	2	High income	H
35	Colombia	COL	Latin America & Caribbean	6	Upper middle income	UM
36	Comoros	COM	Sub-Saharan Africa	1	Lower middle income	LM
37	Mayotte (France)	MYT	Sub-Saharan Africa	1	Upper middle income	UM
38	Congo, Rep.	COG	Sub-Saharan Africa	1	Lower middle income	LM
39	Congo, Dem. Rep.	COD	Sub-Saharan Africa	1	Low income	L
40	Cook Islands	COK	East Asia & Pacific	2	High income	H
41	Costa Rica	CRI	Latin America & Caribbean	6	Upper middle income	UM
42	Croatia	HRV	Europe & Central Asia	3	High income	H
43	Cuba	CUB	Latin America & Caribbean	6	Upper middle income	UM
44	Cyprus	CYP	Europe & Central Asia	3	High income	H
45	Benin	BEN	Sub-Saharan Africa	1	Low income	L

46	Denmark	DNK	Europe & Central Asia	3	High income	H
47	Dominica	DMA	Latin America & Caribbean	6	Upper middle income	UM
48	Dominican Republic	DOM	Latin America & Caribbean	6	Upper middle income	UM
49	Ecuador	ECU	Latin America & Caribbean	6	Upper middle income	UM
50	El Salvador	SLV	Latin America & Caribbean	6	Lower middle income	LM
51	Equatorial Guinea	GNQ	Sub-Saharan Africa	1	Upper middle income	UM
52	Ethiopia	ETH	Sub-Saharan Africa	1	Low income	L
53	Estonia	EST	Europe & Central Asia	3	High income	H
54	Faroe Islands (Denmark)	FRO	Europe & Central Asia	3	High income	H
55	Falkland Isl. (UK)	FLK	Latin America & Caribbean	6	High income	H
56	Fiji	FJI	East Asia & Pacific	2	Upper middle income	UM
57	Finland	FIN	Europe & Central Asia	3	High income	H
58	France	FRA	Europe & Central Asia	3	High income	H
59	French Guiana	GUF	Latin America & Caribbean	6	High income	H
60	French Polynesia	PYF	East Asia & Pacific	2	High income	H
61	Djibouti	DJI	Middle East & North Africa	5	Lower middle income	LM
62	Gabon	GAB	Sub-Saharan Africa	1	Upper middle income	UM
63	Georgia	GEO	Europe & Central Asia	3	Upper middle income	UM
64	Gambia, The	GMB	Sub-Saharan Africa	1	Low income	L
66	Germany	DEU	Europe & Central Asia	3	High income	H

67	Ghana	GHA	Sub-Saharan Africa	1	Lower middle income	LM
68	Gibraltar (UK)	GIB	Europe & Central Asia	3	High income	H
69	Kiribati	KIR	East Asia & Pacific	2	Lower middle income	LM
70	Greece	GRC	Europe & Central Asia	3	High income	H
71	Greenland	GRL	Europe & Central Asia	3	High income	H
72	Grenada	GRD	Latin America & Caribbean	6	Upper middle income	UM
73	Guadeloupe (France)	GLP	Latin America & Caribbean	6	High income	H
74	Guam (USA)	GUM	East Asia & Pacific	2	High income	H
75	Guatemala	GTM	Latin America & Caribbean	6	Upper middle income	UM
76	Guinea	GIN	Sub-Saharan Africa	1	Low income	L
77	Guyana	GUY	Latin America & Caribbean	6	Upper middle income	UM
78	Haiti	HTI	Latin America & Caribbean	6	Low income	L
79	Honduras	HND	Latin America & Caribbean	6	Lower middle income	LM
80	Hong Kong SAR, China	HKG	East Asia & Pacific	2	High income	H
81	Iceland	ISL	Europe & Central Asia	3	High income	H
82	India	IND	South Asia	7	Lower middle income	LM
83	Indonesia	IDN	East Asia & Pacific	2	Lower middle income	LM
84	Iran, Islamic Rep.	IRN	Middle East & North Africa	5	Upper middle income	UM
85	Iraq	IRQ	Middle East & North Africa	5	Upper middle income	UM

86	Ireland	IRL	Europe & Central Asia	3	High income	H
87	Israel	ISR	Middle East & North Africa	5	High income	H
88	Italy	ITA	Europe & Central Asia	3	High income	H
89	Còte d'Ivoire	CIV	Sub-Saharan Africa	1	Lower middle income	LM
90	Jamaica	JAM	Latin America & Caribbean	6	Upper middle income	UM
91	Japan	JPN	East Asia & Pacific	2	High income	H
92	Jordan	JOR	Middle East & North Africa	5	Upper middle income	UM
93	Kenya	KEN	Sub-Saharan Africa	1	Lower middle income	LM
94	Korea, Dem. People's Rep.	PRK	East Asia & Pacific	2	Low income	L
95	Korea, Rep.	KOR	East Asia & Pacific	2	High income	H
96	Kuwait	KWT	Middle East & North Africa	5	High income	H
97	Lebanon	LBN	Middle East & North Africa	5	Upper middle income	UM
98	Latvia	LVA	Europe & Central Asia	3	High income	H
99	Liberia	LBR	Sub-Saharan Africa	1	Low income	L
100	Libya	LBY	Middle East & North Africa	5	Upper middle income	UM
101	Lithuania	LTU	Europe & Central Asia	3	High income	H
102	Macao SAR, China	MAC	East Asia & Pacific	2	High income	H
103	Madagascar	MDG	Sub-Saharan Africa	1	Low income	L
104	Malaysia	MYS	East Asia & Pacific	2	Upper middle income	UM
105	Maldives	MDV	South Asia	7	Upper middle income	UM

106	Malta	MLT	Middle East & North Africa	5	High income	H
107	Martinique (France)	MRT	Latin America & Caribbean	6	Upper middle income	UM
108	Mauritania	MRT	Sub-Saharan Africa	1	Lower middle income	LM
109	Mauritius	MUS	Sub-Saharan Africa	1	Upper middle income	UM
110	Mexico	MEX	Latin America & Caribbean	6	Upper middle income	UM
111	Monaco	MCO	Europe & Central Asia	3	High income	H
112	Montserrat (UK)	MSR	Latin America & Caribbean	6	Upper middle income	UM
113	Morocco	MAR	Middle East & North Africa	5	Lower middle income	LM
114	Mozambique	MOZ	Sub-Saharan Africa	1	Low income	L
115	Oman	OMN	Middle East & North Africa	5	High income	H
116	Namibia	NAM	Sub-Saharan Africa	1	Upper middle income	UM
117	Nauru	NRU	East Asia & Pacific	2	Upper middle income	UM
118	Netherlands	NLD	Europe & Central Asia	3	High income	H
120	Aruba	ABW	Latin America & Caribbean	6	High income	H
121	New Caledonia (France)	NCL	East Asia & Pacific	2	High income	H
122	Vanuatu	VUT	East Asia & Pacific	2	Lower middle income	LM
123	New Zealand	NZL	East Asia & Pacific	2	High income	H
124	Nicaragua	NIC	Latin America & Caribbean	6	Lower middle income	LM
125	Nigeria	NGA	Sub-Saharan Africa	1	Lower middle income	LM

126	Niue (New Zealand)	NIU	East Asia & Pacific	2	Upper middle income	UM
127	Norfolk Isl. (Australia)	NFK	East Asia & Pacific	2	High income	H
128	Norway	NOR	Europe & Central Asia	3	High income	H
130	US Minor Outlying Island	UMI	East Asia & Pacific	2	High income	H
131	Micronesia, Fed. Sts.	FSM	East Asia & Pacific	2	Lower middle income	LM
132	Marshall Islands	MHL	East Asia & Pacific	2	Upper middle income	UM
133	Palau	PLW	East Asia & Pacific	2	High income	H
134	Pakistan	PAK	South Asia	7	Lower middle income	LM
135	Panama	PAN	Latin America & Caribbean	6	High income	H
136	Papua New Guinea	PNG	East Asia & Pacific	2	Lower middle income	LM
137	Peru	PER	Latin America & Caribbean	6	Upper middle income	UM
138	Philippines	PHL	East Asia & Pacific	2	Lower middle income	LM
139	Pitcairn (UK)	PTC	East Asia & Pacific	2	Upper middle income	UM
140	Poland	POL	Europe & Central Asia	3	High income	H
141	Portugal	PRT	Europe & Central Asia	3	High income	H
142	Guinea-Bissau	GNB	Sub-Saharan Africa	1	Low income	L
143	Timor-Leste	TLS	East Asia & Pacific	2	Lower middle income	LM
144	Puerto Rico (USA)	PRI	Latin America & Caribbean	6	High income	H
145	Qatar	QAT	Middle East & North Africa	5	High income	H
146	RÈunion (France)	REU	Sub-Saharan Africa	1	High income	H
147	Romania	ROU	Europe & Central Asia	3	Upper middle income	UM
148	Russian Federation	RUS	Europe & Central Asia	3	Upper middle income	UM
149	Saint Helena (UK)	SHN	Sub-Saharan Africa	1	Upper middle income	UM

150	Saint Kitts & Nevis	KNA	Latin America & Caribbean	6	High income	H
151	Anguilla (UK)		Latin America & Caribbean	6	High income	H
152	Saint Lucia	LCA	Latin America & Caribbean	6	Upper middle income	UM
153	Saint Pierre & Miquelon (France)	SPM	North America	4	High income	H
154	Saint Vincent & the Grenadines	VCT	Latin America & Caribbean	6	Upper middle income	UM
155	SaoTome and Principe	STP	Sub-Saharan Africa	1	Lower middle income	LM
156	Saudi Arabia	SAU	Middle East & North Africa	5	High income	H
157	Senegal	SEN	Sub-Saharan Africa	1	Lower middle income	LM
158	Seychelles	SYC	Sub-Saharan Africa	1	High income	H
159	Sierra Leone	SLE	Sub-Saharan Africa	1	Low income	L
160	Singapore	SGP	East Asia & Pacific	2	High income	H
161	Vietnam	VNM	East Asia & Pacific	2	Lower middle income	LM
162	Slovenia	SVN	Europe & Central Asia	3	High income	H
163	Somalia	SOM	Sub-Saharan Africa	1	Low income	L
164	South Africa	ZAF	Sub-Saharan Africa	1	Upper middle income	UM
165	Spain	ESP	Europe & Central Asia	3	High income	H
167	Sudan	SDN	Sub-Saharan Africa	1	Lower middle income	LM
168	Suriname	SUR	Latin America & Caribbean	6	Upper middle income	UM
169	Sweden	SWE	Europe & Central Asia	3	High income	H

170	Syrian Arab Republic	SYR	Middle East & North Africa	5	Low income	L
171	Thailand	THA	East Asia & Pacific	2	Upper middle income	UM
172	Togo	TGO	Sub-Saharan Africa	1	Low income	L
173	Tokelau (New Zealand)	TKL	East Asia & Pacific	2	Upper middle income	UM
174	Tonga	TON	East Asia & Pacific	2	Upper middle income	UM
175	Trinidad and Tobago	TTO	Latin America & Caribbean	6	High income	H
176	United Arab Emirates	ARE	Middle East & North Africa	5	High income	H
177	Tunisia	TUN	Middle East & North Africa	5	Lower middle income	LM
178	Turkey	TUR	Europe & Central Asia	3	Upper middle income	UM
179	Turks and Caicos Islands (UK)	TCA	Latin America & Caribbean	6	High income	H
180	Tuvalu	TUV	East Asia & Pacific	2	Upper middle income	UM
181	Ukraine	UKR	Europe & Central Asia	3	Lower middle income	LM
182	Egypt, Arab Rep.	EGY	Middle East & North Africa	5	Lower middle income	LM
183	United Kingdom	GBR	Europe & Central Asia	3	High income	H
184	Channel Islands	CHI	Europe & Central Asia	3	High income	H
185	Isle of Man (UK)	IMN	Europe & Central Asia	3	High income	H
186	Tanzania	TZA	Sub-Saharan Africa	1	Low income	L
187	United States	USA	North America	4	High income	H
188	Virgin Islands (U.S.)	VIR	Latin America & Caribbean	6	High income	H

189	Uruguay	URY	Latin America & Caribbean	6	High income	H
190	Venezuela	VEN	Latin America & Caribbean	6	Upper middle income	UM
191	Wallis & Futuna Isl. (France)		East Asia & Pacific	2	Upper middle income	UM
192	Samoa	WSM	East Asia & Pacific	2	Upper middle income	UM
193	Yemen, Rep.	YEM	Middle East & North Africa	5	Low income	L
194	Montenegro	MNE	Europe & Central Asia	3	Upper middle income	UM
195	Crozet Isl. (France)	CRO	Sub-Saharan Africa	1	High income	H
196	Kerguelen Isl. (France)	KER	Sub-Saharan Africa	1	High income	H
199	Svalbard Isl. (Norway)	SJM	Europe & Central Asia	3	High income	H
200	Alaska (USA)	USA	North America	4	High income	H
208	South Cyprus	CYP	Europe & Central Asia	3	High income	H
209	Saint Barthelemy (France)	BLM	Latin America & Caribbean	6	High income	H
210	Saint Martin (French part)	MAF	Latin America & Caribbean	6	High income	H
214	CuraÁao	CUW	Latin America & Caribbean	6	High income	H
215	Sint Maarten (Dutch part)	SXM	Latin America & Caribbean	6	High income	H
217	Madeira Isl. (Portugal)	MDR	Europe & Central Asia	3	High income	H
218	Azores Isl. (Portugal)		Europe & Central Asia	3	High income	H
221	Saba and Saint Eustatius (Netherlands)	BES	Latin America & Caribbean	6	High income	H

222	Bonaire (Netherlands)	BES	Latin America & Caribbean	6	High income	H

Table S2. Countries that are not included in this study.

Fishing Entity ID	Country Name
17	Brit. Indian Ocean Terr. (UK)
33	Christmas Isl. (Australia)
34	Cocos (Keeling) Isl. (Australia)
37	Mayotte (France)
40	Cook Islands
55	Falkland Isl. (UK)
59	French Guiana
73	Guadeloupe (France)
107	Martinique (France)
112	Montserrat (UK)
126	Niue (New Zealand)
127	Norfolk Isl. (Australia)
139	Pitcairn (UK)
146	Réunion (France)
149	Saint Helena (UK)
151	Anguilla (UK)
153	Saint Pierre & Miquelon (France)
173	Tokelau (New Zealand)
191	Wallis & Futuna Isl. (France)
207	North Cyprus*
208	South Cyprus*
209	St Barthelemy (France)
210	St Martin
213	Unknown Fishing Country
217	Madeira Isl. (Portugal)
218	Azores Isl. (Portugal)
219	Ascension Isl. (UK)
220	Tristan da Cunha Isl. (UK)
221	Saba and Saint Eustaius (Netherlands)
222	Bonaire (Netherlands)
223	Fishing Country Unknown

*South and North Cyprus are grouped as Cyprus in this analysis.

Table S3. Functional groups in the SAU catch database.

Name	Description
Other	Other
pelagicsm	Small Pelagics (<30 cm)
pelagicmd	Medium Pelagics (30 - 90 cm)
pelagiclg	Large Pelagics (>=90 cm)
demersalsm	Small Demersals (<30 cm)
demersalmd	Medium Demersals (30 - 90 cm)
demersallg	Large Demersals (>=90 cm)
bathypelagicsm	Small Bathypelagics (<30 cm)
bathypelagicmd	Medium Bathypelagics (30 - 90 cm)
bathypelagiclg	Large Bathypelagics (>=90 cm)
bathydemersalsm	Small Bathydemersals (<30 cm)
bathydemersalmd	Medium Bathydemersals (30 - 90 cm)
bathydemersallg	Large Bathydemersals (>=90 cm)
benthopelagicsm	Small Benthopelagics (<30 cm)
benthopelagicmd	Medium Benthopelagics (30 - 90 cm)
benthopelagiclg	Large Benthopelagics (>=90 cm)
reef-associatedsm	Small Reef assoc fish (<30 cm)
reef-associatedmd	Medium Reef assoc fish (30 - 90 cm)
reef-associatedlg	Large Reef assoc fish (>=90 cm)
sharksm-md	Small to Medium Sharks (<90 cm)
sharklg	Large Sharks (>=90 cm)
raysm md	Small to Medium Rays (<90 cm)
raylg	Large Rays (>=90 cm)
flatfishsm md	Small to Medium Flatfishes (<90 cm)
flatfishlg	Large Flatfishes (>=90 cm)
cephalopods	Cephalopods
shrimp	Shrimps
lobsters,crab	Lobsters, Crabs
jellyfish	Jellyfish
otherdeminvert	Other Demersal Invertebrates
krill	Krill

Opportunity cost of capital

For all European countries that had data available from the 2016 STECF dataset (see summary report here: https://stecf.jrc.ec.europa.eu/c/document_library/get_file?uuid=f519adc4-c5cf-4b0a-9fd5-0dd7b3108974&groupId=43805), we were able to estimate opportunity costs using the formula they provided in the report. For each year, the European dataset has "Tangible asset value" (or "vessel depreciated replacement value"), this value was then multiplied by the real interest rate (i.e. r(t) = ((1 + nominal interest rate(t)) / (1 + inflation(t))) -1). Specifically, we used the annual long-term interest rate (government bonds maturing in 10 years) available from the OECD library to compute the nominal interest rate i. As for the year to year inflation statistics, we also used the OECD database for most European countries (using consumer price index trends) with 2015 as their base year. We extracted inflation data from Eurostat with regard to Bulgaria, Croatia, Cyprus, Malta and Romania.

We then multiplied the tangible asset value with the real interest rate each year and this gave us the opportunity cost in the database. The report mentioned: "In particular STECF observes that the use of real interest rate can lead to negative rates hence for some countries resulting in negative opportunity cost of capital which gives estimates with higher net than the gross profits." So, the negative sign of the opportunity cost of capital comes mainly from the negative real interest that we get in some years. We interpreted it as such that the action taken (i.e. using the boat for fishing activities) is better than the alternative of putting the replacement or tangible value of the ship/vessel into the bank and earning interest on it. We still keep these negative opportunity costs in the observed fishing cost database as it's interesting to consider them in the later stage. But we removed them (convert them to zero) for the gap filling purpose and in our final database as the negative utility for the alternative options should not be considered.

Other non-EU countries that showed information on opportunity costs of capital were Fiji and Palau. Computing the real interest rate and estimating the OC with the tangible asset value was only specific to EU countries. Fiji and Palau's data tables had particular estimates available for the OC so no need for calculations in those cases.

Table S4. Number of raw fishing subsidy data points in each income group.

Income Group	Number of data points
High	2015
Low	385
Lower medium	1002
Upper medium	966

Table S5. Number of raw fishing data points for each subsidy types.

Class	Subsidy types	Number of data points
A1	Monitoring control & surveillance programs	1022
A2	Research & development	243
A3	MPAs	154
B1	Financial support towards fleet renewal & modernization	379
B2	Development grants for fishery projects	1021
B3	Port & harbour construction & renovation programs	213
B4	Marketing support, processing & storage infrastructure programs	414
B5	Tax Exemptions	81
B6	Foreign Access Agreements	171
B7	Fuel	123
C1	Income support programs	372
C2	Other decommissioning programs	103
C3	Rural fisheries community development Programs	72

Table S6

Region ID	Region	Fuel use intensity (FUI) ($tFuel \cdot tCatch^{-1}$)
1	Africa	0.69
2	Asia	0.88
3	Europe	0.36
4	North America	0.33
5	Oceania	0.31
6	South, Central America and Caribbean	0.16

*source of data is from Greer *et al.* (2019).

Table S7. Projected fisheries private rents and change in fisheries private rents relative to the current status (%) under two different scenarios in the near future (2030s), mid-century (2050s) and the end of this century (2100s) of different income groups.

Income groups	Current Private Rents (billions, USD)	Mean private rent under SSP1-2.6 (billions, USD)			Mean private rent under SSP5-8.5 (billions, USD)		
		2030s	2050s	2100s	2030s	2050s	2100s
Low income	0.77	0.83 (7.3)	0.81 (4.6)	0.86 (11.1)	0.78 (1.3)	0.78 (0.8)	0.47 (-38.6)
Lower middle income	3.07	1.59 (-48.2)	0.38 (-87.6)	0.61 (-80.2)	2.55 (-16.9)	1.52(-50.4)	-0.78 (-125.5)
Upper middle income	23.47	22.41 (-4.5)	21.47 (-8.5)	22.42 (-4.5)	23.06 (-1.8)	22.06 (-6.0)	18.00 (-23.3)
High income	13.28	12.63 (-4.9)	12.83 (-3.4)	13.85 (4.3)	12.85 (-3.2)	12.73 (-4.1)	7.04 (-47.0)
Others	0.37	0.24 (-34.0)	0.14 (-62.2)	0.12 (-66.2)	0.26 (-30.2)	0.03 (-92.1)	-0.42 (-215.4)
Grand Total	40.96	37.70 (-8.0)	35.62 (-13.0)	37.86 (-7.6)	39.50 (-3.6)	37.12 (-9.4)	24.30 (-40.7)

Table S8. Projected fisheries economic rents and change in fisheries economic rents relative to the current status (%) under two different scenarios in the near future (2030s), mid-century (2050s) and the end of this century (2100s) of different income groups.

Income groups	**Current Economic Rents (billions, USD)**	**Mean economic rent under SSP1-2.6 (billions, USD)**			**Mean economic rent under SSP5-8.5 (billions, USD)**		
		2030s	**2050s**	**2100s**	**2030s**	**2050s**	**2100s**
Low income	0.24	0.29 (23.8)	0.27 (15.0)	0.32 (36.3)	0.25 (4.2)	0.24 (2.8)	-0.06 (-126.3)
Lower middle income	1.02	-0.46 (-144.5)	-1.67 (-262.8)	-1.44 (-240.6)	0.50 (-50.9)	-0.52 (-151.2)	-2.83 (-376.7)
Upper middle income	15.16	14.09 (-7.0)	13.15 (-13.2)	14.10 (-7.0)	14.74 (-2.7)	13.74 (-9.3)	9.68 (-36.1)
High income	7.85	7.20 (-8.3)	7.40 (-5.7)	8.42 (7.3)	7.42 (-5.5)	7.30 (-7.0)	1.61 (-79.5)
Others	0.37	0.24 (-34.0)	0.14 (-62.2)	0.12 (-66.2)	0.26 (-30.2)	0.03 (-92.1)	-0.42 (-215.4)
Grand Total	24.63	21.36 (-13.3)	19.29 (-21.7)	21.52 (-12.6)	23.16 (-5.9)	20.78 (-15.6)	7.97 (-67.7)

*Economic rents is the total fishing costs and capacity enhancing subsidies (fuel subsidies, tax exemption and subsidies for fishing access to other countries) subtracted by the total landed values.

Table S9. Projected fisheries private rents and change in fisheries private rents relative to the current status (%) under two different scenarios in the near future (2030s), mid-century (2050s) and the end of this century (2100s) of different regions.

Regions	Current Private Rents (billions, USD)	Mean Private rents under SSP1-2.6 (billions, USD)			Mean Private rents under SSP5-8.5 (billions, USD)		
		2030s	2050s	2100s	2030s	2050s	2100s
East Asia & Pacific	16.70	14.81 (-11.3)	12.76 (-23.6)	14.28 (-14.5)	15.85 (-5.1)	13.41 (-19.7)	8.69 (-48.0)
Europe & Central Asia	6.77	6.81 (0.6)	7.07 (4.5)	8.36 (23.5)	6.81 (0.6)	7.91 (16.9)	6.77 (0.1)
Latin America & Caribbean	9.03	8.68 (-3.8)	8.79 (-2.6)	8.72 (-3.4)	8.79 (-2.6)	8.78 (-2.7)	6.63 (-26.5)
Middle East & North Africa	1.12	1.02 (-8.2)	1.09 (-2.7)	1.17 (4.6)	1.09 (-2.7)	1.15 (2.9)	0.67 (-40.3)
North America	5.11	4.68 (-8.5)	4.67 (-8.7)	3.80 (-25.7)	4.95 (-3.3)	4.17 (-18.4)	1.15 (-77.5)
South Asia	0.58	0.58 (0.6)	0.51 (-11.3)	0.56 (-2.6)	0.61 (6.4)	0.64 (11.8)	0.49 (-14.4)
Sub-Saharan Africa	1.29	0.88 (-31.9)	0.60 (-53.9)	0.84 (-34.8)	1.15 (-11.0)	1.03 (-20.4)	0.32 (-75.3)
Others	0.37	0.24 (-34.0)	0.14 (-62.2)	0.12 (-66.2)	0.26 (-30.2)	0.03 (-92.1)	-0.42 (-215.4)
Grand Total	40.96	37.70 (-8.0)	35.62 (-13.0)	37.86 (-7.6)	39.50 (-3.6)	37.12 (-9.4)	24.30 (-40.7)

Table S10. Projected fisheries economic rents and change in fisheries economic rents relative to the current status (%) under two different scenarios in the near future (2030s), mid-century (2050s) and the end of this century (2100s) of different regions.

Regions	Current Economic Rents (billions, USD	Mean economic rent under SSP1-2.6 (billions, USD)			Mean economic rent under SSP5-8.5 (billions, USD)		
		2030s	2050s	2100s	2030s	2050s	2100s
East Asia & Pacific	7.72	5.82 (-24.5)	3.77 (-51.1)	5.29 (-31.4)	6.87 (-11.0)	4.42 (-42.7)	-0.30 (-103.9)
Europe & Central Asia	2.72	2.75 (1.4)	3.02 (11.3)	4.31 (58.7)	2.75 (1.4)	3.86 (42.0)	2.72 (0.1)
Latin America & Caribbean	8.06	7.71 (-4.3)	7.82 (-2.9)	7.75 (-3.8)	7.82 (-3.0)	7.81 (-3.0)	5.66 (-29.7)
Middle East & North Africa	0.68	0.59 (-13.5)	0.65 (-4.5)	0.73 (7.7)	0.65 (-4.4)	0.71 (4.8)	0.23 (-66.4)
North America	4.41	3.97 (-9.9)	3.96 (-10.1)	3.09 (-29.8)	4.24 (-3.8)	3.47 (-21.4)	0.45 (-89.9)
South Asia	0.37	0.38 (0.9)	0.31 (-17.5)	0.36 (-4.1)	0.41 (9.9)	0.44 (18.2)	0.29 (-22.3)
Sub-Saharan Africa	0.31	-0.10 (-131.5)	-0.38 (-221.8)	-0.14 (-143.1)	0.17 (-45.3)	0.05 (-83.9)	-0.66 (-310.2)
Others	0.37	0.24 (-34.0)	0.14 (-62.2)	0.12 (-66.2)	0.26 (-30.2)	0.03 (-92.1)	-0.42 (-215.4)
Grand Total	24.63	21.36 (-13.3)	19.29 (-21.7)	21.52 (-12.6)	23.16 (-5.9)	20.78 (-15.6)	7.97 (-67.7)

*Economic rents is the total fishing costs and capacity enhancing subsidies (fuel subsidies, tax exemption and subsidies for fishing access to other countries) subtracted by the total landed values.

Stock status scores and fisheries management index from OHI

We also extracted the stock status scores from the Ocean Health Index (OHI) website. The scores are calculated from the ratio of biomass(B) to biomass at maximum sustainable yield (BMSY) i.e., B/BMSY values of each stocks in each country and weighted by the catch of each stock. For details of the methods, please refer to Ocean Health Index website[2]. Also, we extracted the fisheries management index of each country from the OHI website. The index indicates the effectives of fisheries management measures in each country. Details of this index can be found on the OHI website[3]. By using these indices, we can assess the stock status and fisheries management effectiveness in each country.

[2] Ocean Health Index2020: Methods (https://htmlpreview.github.io/?https://github.com/OHI-Science/ohi-global/published/documents/methods/Supplement.html#661_fisheries_(subgoal_of_food_provision))
[3] OHI 2019 – Fisheries Management Index (Resilience) (http://ohi-science.org/ohiprep_v2020/globalprep/res_fmi/v2019/fmi_data_prep.html)