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Assessment of global fish footprint reveals growing challenges for sustainable production and consumption

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ABSTRACT

Globalization faces a tradeoff between meeting fish consumption demand for nutritious & healthy living and reducing the ecological footprint to achieve sustainable development. Here, we document drivers, historical trends, and mitigation options for global fish footprint using unevenly spaced data spanning 1961 to 2021 from over 200 economies while accounting for income classifications. We report a decline in fish production in developed countries, yet, their increased consumption demand per capita is met through overexploited stocks of fish imported from developing economies. Besides, global fish price volatility has no effect on fish distribution in high-income nations but highly influences fish production, consumption, import, and export in developing nations. The evidence of purchasing economies of scale in urbanized countries and the potential threat of embodied price in fish distribution and trade affect global fish footprint. The persistent increase in fish footprint can be attributed to affluence, choice of technology, urbanization, human development, marine trophic levels, emission intensity, and time-invariant & unobserved country-specificities. We highlight that aligning development and choices along the targets of sustainable development goals augments the achievement of sustainable fish production and consumption.

1. Introduction

Food is a basic need for human survival—hence, its availability, accessibility, and affordability remain crucial to achieving food security (Nicholson et al., 2020). However, the growing production and consumption rate of global food resources undermines environmental sustainability (Garnett, 2013). Humanity is faced with several environmental challenges that require urgent climate-resilient options including mitigation and adaptation to reduce climate vulnerabilities (Sarkodie et al., 2022). However, stringent measures that contravene present global demand may be detrimental to sustained economic pathways (Schandl et al., 2020). The tradeoff between reducing environmental challenges and meeting present demands without jeopardizing sustainable economic development remains crucial in the era of globalization. Recent studies developed a framework that links the synergies and tradeoffs of the sustainable development goal (SDG) 14 — the "ocean goal" — to the other 16 SDGs (Frazão Santos et al., 2020; Singh et al., 2018). Yet, literature that comprehensively documents the complex interactions of fish footprint in line with the targets of the SDGs is limited. Accurate accounting of such complex dynamics and the magnitude of effects is crucial to designing sustainable fish resource policies while attaining the other SDGs.

Here, we present a global fish footprint of nations using several indicators of sustainability (see Table 1) by assessing the drivers, temporal trends, and mitigation options while accounting for income convergence. We specifically examine the impact of fish availability, accessibility, and affordability on global fish footprint across global economies and income groups. Our study investigates research questions including, (1) Are historical trends in fish production and consumption indicative of fish overexploitation or collapse? (2) Is there trade convergence that influences fish distribution? (3) Which economies have fish reserves or nearing fish deficits? and (4) What are the global drivers of fish footprint? We use estimation techniques such as wavelet analysis that account for transient characteristics in ecological components via time-frequency localization, and machine learning-based econometric technique that accounts for nonlinearity, time-invariant and unobserved heterogeneous effects, and temporal effects across over 200 countries and territories. We find persistent effects of fish footprint attributed to historical consumption patterns across income classifications, especially in high-income economies. Upsurge in global fish consumption per

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Table 1
Variable collection, description & SDG linkages.

Variable name	SDG target[a]	Period	Units	Source/reference	
Response variable					
Fish footprint - ecological footprint of consumption	SDG 14.4: Reduce harvesting & overfishing.	1995–2017	GHA/person	Quality of Government Institute	https://buff.ly/3uqJIFB
Shift estimation					
Fish biocapacity per capita	SDG 14.2: Protect & restore the marine ecosystem.	1961–2016	GHA/capita	Quality of Government Institute	https://buff.ly/3uqJIFB
Fish stock status	SDG 14.4: End overfishing & restore fish stock.	1995–2020	Score	Sea Around Us	https://buff.ly/3uAwshL
Ecological fish status	SDG 14.7: Sustainable fisheries management.	1961–2016	Score	In this paper	Authors
Fish export in developing countries	SDG 17.11: increase share of global exports.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Fish consumption in developing countries	SDG 12.2: domestic material consumption.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Fish import in developing countries	SDG 17.12: enhanced market access.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Fish production in developing countries	SDG 12.1: shift to sustainable production.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Human consumption of fish per capita in developing countries	SDG 12.2: domestic material consumption per capita	1990–2021	kg/capita	OECD	https://buff.ly/3nGykS1
Fish export in developed countries	SDG 17.4: debt sustainability financing.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Fish consumption in developed countries	SDG 8.4.2: domestic material consumption.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Fish import in developed countries	SDG 17.13: enhanced economic stability.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Fish production in developed countries	SDG 12.1: shift to sustainable production.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Human consumption of fish per capita in developed countries	SDG 8.4.2: domestic material consumption per capita.	1990–2021	kg/capita	OECD	https://buff.ly/3nGykS1
Global fish export	SDG 17.4: debt sustainability financing.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Global fish consumption	SDG 8.4: global resource efficiency in consumption.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Global fish import	SDG 17.13: enhanced global economic stability.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Global fish production	SDG 8.4: global resource efficiency in production.	1990–2021	Tonnes, thousands	OECD	https://buff.ly/3nGykS1
Global human consumption of fish per capita	SDG 8.4.2: global material consumption per capita.	1990–2021	kg/capita	OECD	https://buff.ly/3nGykS1
World fish price	SDG 2.c: proper food commodity markets & limiting extreme food price volatility.	1990–2021	US$/tonne	OECD	https://buff.ly/3nGykS1
Independent variables					
1. Socio-economic					
Human development index	SDG 4.7; 12.8: sustainable development & lifestyle.	1995–2017	Index	UNDP	https://buff.ly/3CK5iYh
GDP per capita	SDG 1.1; 8.1-2: eradicate poverty & sustained income.	1995–2017	constant 2015 US$	World Bank	https://buff.ly/3ic6nik
Foreign direct investment net inflows	SDG 8.9; 9.a; 17.18-19: sustainable tourism, technology diffusion & external funding.	1995–2017	BoP, current US$	IMF, Balance of Payments database	https://buff.ly/3ic6nik
2. Demographics					
Population, total	SDG 10.1-5: sustained income with reduced inequality.	1995–2017	Number	World Bank	https://buff.ly/3ic6nik
Urban population	SDG 11.3; 11.a: sustainable urbanization.	1995–2017	Number	World Bank	https://buff.ly/3ic6nik
Rural population	SDG 11.a: improved social, economic & environmental links between rural and urban areas.	1995–2017	Number	World Bank	https://buff.ly/3ic6nik
3. Technology					
Energy use	SDG 7.3: improve energy efficiency.	1995–2017	kgoe/capita	OECD/IEA	https://buff.ly/3Rch30D
Fossil fuel energy consumption	SDG 12.2: sustainable & efficient use of resources.	1995–2017	% of total	IEA	https://buff.ly/3Rch30D
4. Biodiversity					
Marine trophic index	SDG 14.4: reducing effects of fishing on fish stocks.	1995–2017	Index	Quality of Government Institute	https://buff.ly/3uqJIFB
5. Environment					
Climate change vulnerability	SDG 13.1: climate-resilience & adaptive capacity.	1995–2017	Score	NDGAIN	https://buff.ly/3OLDHLP
Average annual temperature	SDG 2.4; 13.1: reducing extreme climate hazards.	1995–2017	°C	Yuan et al. (2021)	https://buff.ly/3PnTIHN
Average annual precipitation	SDG 2.4; 13.1: reducing extreme weather—drought & flooding.	1995–2017	mm/year	Yuan et al. (2021)	https://buff.ly/3PnTIHN
Greenhouse gas emissions	SDG 13.2-3: climate change mitigation & impact reduction.	1995–2017	Mton CO_2eq	Emission Database for Global Atmospheric Research	https://buff.ly/3ReNawA

[a] (United Nations, 2021).

capita in high-income nations amidst low fish biocapacity implies fish stocks in developing countries become a source of exploitation to meet demands in developed countries, thus, exacerbating fish footprint. Demographic dynamics of consumption patterns confirm the mitigating effects of ruralization and escalation effects of urbanization on global fish footprint.

2. Methods

2.1. Data

We gathered time series and unevenly spaced cross-sectional time series datasets spanning 1961–2021 (see Table 1). Because our analyses hinge on the credibility of secondary datasets, we employed data from high-quality sources detailed in Table 1. The Quality of Government (QoG) Standard datasets involve a meticulous data collection process from a wide range of existing data sources, surveys, expert assessments, and administrative records. Data aggregation and harmonization, and data validation and quality control techniques are applied to these sourced data to ensure the reliability and accuracy of the datasets (Teorell et al., 2021). Our datasets entail over 200 countries and territories (see Supplementary Table 1, economies are identified using both names & ISO3 code), 4 income (low, lower-middle, upper-middle, & high) groups, and 2 economic (developed & developing) classifications. The first dataset (time series & panel data) comprises fish biocapacity, fish stock status, ecological fish status, fish production, consumption, imports, exports, and the global fish price used to examine historical shifts. Additionally, the ecological time series sample in the first dataset is used for decomposition analysis and time series relationships. The second dataset (panel data only) employs fish footprint as the target variable whereas—the predictors include climate change vulnerability, human development index (HDI), GDP per capita, total population, rural & urban population, foreign direct investment (FDI), energy use, fossil fuels, marine trophic index, GHG emissions, and average temperature & precipitation with $0.5^{\circ} \times 0.5^{\circ}$ spatial resolution (Table 1). Our several independent variables can be classified broadly under socio-economic, demographics, technology, biodiversity, and environment. The socio-economic classification details the effect of income (poverty vs. wealth), external funding (resource-efficient vs. resource-intensity), and human development (captures inequality in standard of living, education & life expectancy [low human development vs. high human development]) on the dynamics of fish footprint. The varying supply and demand of marine resources are largely driven by population dynamics namely ruralization and urbanization, which determine the extent of resource exploitation and management. Energy plays a vital role in fisheries, yet, the technological composition (renewables or fossil fuels) determines the sustainability of the marine ecosystem. The marine trophic index is a useful biodiversity indicator for assessing the effect of fishing on fish stocks (Butchart et al., 2010). The environmental variables involve climatic events and underlying drivers that may alter the dynamics of fish resources (Wernberg et al., 2013). These sampled variables align with several targets and indicators of the Sustainable Development Goals (SDGs)—depicting factors that affect the demographics, economics, health, and the environmental sustainability dimension of the marine ecosystem. The integration of the SDGs from various sectors allows the assessment of the potential synergies and trade-offs associated with the supply and demand of fish resources (Table 1). For example, in the adoption of global fish prices, we can assess the effect of (extreme) food price volatility (as outlined in SDG 2.c.) on sustainable production & consumption of fish resources. Similarly, SDG 14 is a broader context that captures the progress towards achieving ocean sustainability and conserving the marine ecosystem by reducing the accelerated threats of acidification, eutrophication, fishery collapse, ocean warming, and marine pollution. Here, we narrow the several ocean sustainability threats to fish footprint, which measures the biologically productive fishing grounds required to produce the maximum sustainable and harvestable catch of fish species using existing technologies and resource management techniques (Teorell et al., 2021). This implies that increasing demand for fish-related resources above a country's ability of available fishing grounds to produce seafood (i.e., fish biocapacity) will lead to fishery collapse and deficit.

2.2. Empirical analysis

Ecological fish status was calculated by subtracting fish footprint consumption from fish biocapacity to classify economies under either fishery reserve or fishery deficit—the latter of which is a threat to biodiversity and the sustainable fish sector. We subsequently examined historical changes (i.e., shift estimation) in fish stock, harvesting & restoration (i.e., fish stock, fish footprint consumption & biocapacity) across economies and fish distribution & trade across income classification over time. Adopting this technique is crucial to assess the rate of fish exploitation, market access, economic stability (including debt sustainability financing), and sustainable fisheries management (resource efficiency, domestic material production & consumption). The shift estimation was derived using panel data operators that capture both first-difference and historical effects using the expression:

$$Shift_{i,t}\,(\%) = 100 \times \left(\frac{x_{i,t} - x_{i,t-1}}{x_{i,t-1}}\right)$$

We further generated normalized mean samples from the cross-sectional time series dataset while controlling for time periods across economies, which is expressed as:

$$\overline{Shift_{i,t}} = \left(\frac{1}{W}\sum_{j=1}^{n} w_j y_j\right)_i$$

$$X_{i,t}^{Norm} = 100 \times \left[\frac{x_{i,t} - min(x_i)}{max(x_i) - min(x_i)}\right]$$

where the first-difference of variable x (i.e., $x_{i,t} - x_{i,t-1}$) is divided by 1-period (t) lag of x across country i, $\overline{Shift}$ is the mean of the estimated yearly shift, W is the sum of individual ($j = 1, \ldots, n$) weights (w_j), n denotes the sample size, y_j is the individual observations of the estimated variable y, $min(x_i)$, and $max(x_i)$ represent minimum & maximum data points. We use the minimum-maximum normalization ($Norm$) to generate further datasets for between-income-group pairwise comparison and statistical visualization.

In line with SDG 2.c, we assessed the effect of extreme fish price volatility on fish production, consumption, and trade (i.e., imports & exports) using the expression:

$$Ratio_{k,t} = \Delta Y_{k,t} / \Delta Price_t$$

where $Ratio_{k,t}$ denotes the average rate of change across income classifications k (i.e., developing vs. developed countries) over the sampled period t (1990–2021), $\Delta Y_{k,t} = \left(Y_{k,t} - Y_{k,t-1}/Y_{k,t-1}\right) \times 100$ represents the individual returns of fish distribution Y [namely production, consumption, imports, and exports], whereas $\Delta Price_t = (Price_t - Price_{t-1}/Price_{t-1}) \times 100$ is the global fish price returns.

2.3. Model estimation

The econometric techniques applied include both time series and panel data models. For the time series modeling, we applied bivariate wavelet coherence to examine the nexus between variability in fish trade & distribution and global fish price volatility. The wavelet analysis involves a time-frequency localization applicable to nonstationary systems (typically tested using unit root methods), like the transitory components (that violated the assumption of stationarity) observed in our ecological indicators (Sarkodie et al., 2023). We employed the Morlet wavelet—a continuous wavelet approach as the choice of mother wavelet (the decomposed signals over translated function) due to its good scale & frequency localization, and robustness to noise (Cazelles et al., 2007). Besides, the decomposition function of the estimation approach has the ideal tradeoff between time and frequency resolution, suitable for assessing aperiodic dynamics, chaotic components, and short-lived signals (Cazelles et al., 2008). Prior literature applied this technique to investigate the effect of environmental forcing and population dynamics on the variations in fisheries observed in the Atlantic (Rouyer et al., 2008). However, the existing traditional wavelet technique applied in the literature produces an artificial and systematically reduced power spectrum at lower periods, thus, the current bivariate wavelet technique used herein employs normalized scales to correct this bias (Liu et al., 2007; Veleda et al., 2012) Using the bivariate wavelet approach, we developed 30 bivariate models across income classifications and validated the estimated results using global dataset.

Second, we developed panel estimation models using a machine learning technique aimed at addressing challenges affecting panel classification and regression devoid of strict parametric assumptions, yet controlling for nonlinearity, heterogeneity, and interaction effects (Hainmueller and Hazlett, 2014). Our panel estimator provides a balance between typical generalized linear models and machine learning, hence, reducing panel misspecification bias while improving predictability and statistical inferences. Our model specification follows a typical panel fixed-effects model expressed as:

$$fish_{i,t} = \beta_0 + \beta_1 G_{i,t} + \beta_2 G_{i,t}^2 + \beta_3 T_{i,t} + \beta_4 T_{i,t}^2 + \beta_5 V_{i,t} + \delta z_{i,t} + a_i + \varepsilon_{i,t}$$

where model 1 incorporates β_0 as the intercept, $fish_{i,t}$ denotes the target variable (fish footprint), $G_{i,t}$ & $G_{i,t}^2$ represent income level and quadratic of income to examine the doubling effect of sustained income in economies i and year t (the selection of the period [i.e., 1961–2017] is because our panel data analysis requires a balanced dataset [without missing values in other variables] for all variables incorporated in the model for consistency and accuracy), $T_{i,t}$ & $T_{i,t}^2$ represent the low and high mean annual temperature effects, $V_{i,t}$ is the vulnerability to climate change, a_i captures unobserved and time-invariant country-specific fixed effects that account for time-invariant heterogeneity affecting fish footprint. The notation $\varepsilon_{i,t}$ is the time-varying idiosyncratic error whereas $z_{i,t}$ denotes other control variables namely ruralization, urbanization, energy use, precipitation, time trends, and quadratic of time trends by economies to capture changes in technology and innovation. This equation was further used to test the fish footprint Kuznets curve (F^2KC) hypothesis while accounting for income convergence (this was further validated with a third model with only income, quadratic of income, time trends, and quadratic of time trends by economies). Investigating the validity of F^2KC hypothesis is crucial because while poor economies consume more fish resources due to the inability to afford meat and meat products, wealthy countries consume more fish to improve their healthy lifestyle while reducing diet-attributed morbidity and mortality (Hirvonen et al., 2020).

$$fish_{i,t} = \beta_0 + \beta_1 fish_{i,t-1} + \beta_2 FDI_{i,t} + \beta_3 FDI_{i,t}^2 + \beta_4 E_{i,t} + \delta z_{i,t} + a_i + \varepsilon_{i,t}$$

In the second model, $fish_{i,t-1}$ is the lagged fish footprint to assess historical change and initial effects, $FDI_{i,t}$ & $FDI_{i,t}^2$ represent foreign direct investment inflows to assess potential spillover effects of external funding, $E_{i,t}$ is greenhouse gas emissions, used as a proxy indicator to examine the effects of climate change on fish footprint, $z_{i,t}$ represents other control variables including human development, marine trophic level, and lagged fossil fuel consumption (i.e., the persistent growth of fossil fuel utilization underpins industrialization and economic productivity in several economies). The notations $\beta_1 \dots \beta_p$ & δ are the estimated parameters whereas a_i captures unobserved country effects and temporal effects that may bias the model estimates. The robustness of the estimated models is improved by further specifying the pointwise estimates to include unconditional distribution across quantiles. The integration of quadratic terms in both models highlights the response of fish footprint to nonlinearity in income, temperature, and investment inflows. We improved the numerical precision of the included second-degree polynomials (i.e., trend, trend^2, income, income^2, FDI, FDI^2, Temperature, and Temperature^2) by generating orthogonal variables of the original series using the Christoffel-Darboux recurrence technique (Abramowitz and Stegun, 1964). This serves two estimation advantages namely controlling for collinearity and exclusively retaining the effects of all series (Golub and Van Loan, 2013).

2.4. Caveats

Due to data convenience, we employed unevenly spaced datasets with different time periods, however, we used estimation methods that control for such limitations. For the wavelet analysis, we only used aggregated data based on income classification, hence, unable to assess country-specific variations compared to the panel data models. Yet, this shortfall still provides an opportunity to examine the role of income convergence on the nexus between fish trade & distribution and fish price volatilities. Second, there are several socio-economic, technological innovation, and demographic factors that were not considered in our models, however, the inclusion of country-specific, time-specific, time trends, heterogeneous and lagged-dependent variables account for such time-varying factors while controlling for unobserved and omitted-variable biases (Wooldridge, 2016).

3. Results

3.1. Trends in fish distribution

We used statistical visualizations to investigate the current patterns of fish distribution and trade dynamics. Global fish production increased by 84.17 % between 1990 and 2021, however, developing countries observed 166.11 % growth [i.e., 56,484.83 to 150,313.53 (thousand tonnes)] in production compared to ~28 % yield in developed countries. Interestingly, the ratio of mean fish output in developing countries to the mean yield in developed economies is about 3.4 times. While historical production appears to decline in developed countries, a contrary case is observed in developing countries (Fig. 1a). As of 2021, the top 10 fish producers that account for 68.88 % of global fish production include China (65,552 thousand tonnes, indicating 42.54 % of global fish output), Indonesia, India, Vietnam, Peru, the US, Russia, Norway, Japan, and Chile (Supplementary Table 2). Similarly, global fish consumption grew from 98,784 (thousand tonnes in 1990) to 180,075 (thousand tonnes in 2021), representing 82.29 % increase in 32 years. Fish consumption in developing countries increased by 163.14 % but declined by 17.3 % [i.e., 44,254.81 in 1990 to 36,586.98 in 2021 (thousand tonnes)] in developed countries. This implies developing countries consume 2.65 times more fish on average than developed economies (Supplementary Fig. 1b). The top 10 fish consumers representing 66.32 % of global fish consumption comprise China (59,859 thousand tonnes, indicating 41.62 % of global fish consumption as of 2021), Indonesia, India, the US, Japan, Vietnam, Peru, Russia, Korea, and the Philippines (Supplementary Table 3). When we control for population, human consumption of fish is on average ~1.47 times higher in developed countries (20.32 kg/capita) than in developing countries (13.78 kg/capita), which outweighs the global average of 15.17 kg/capita. While fish consumption per capita has declined by 22.43 % in developing countries from 1990 to 2021, consumption per capita has increased by 104.87 % (i.e., 8.65 kg/capita in 1990 to 17.72 kg/capita in 2021) in developing countries within the same period (Fig. 1b).

There has been a surge in global fish importation compared to fish exportation. For example, the mean import between 1990 and 2021 is valued at 31,122 (thousand tonnes), nearly 1.02 times compared to mean fish export [i.e., 30,640 (thousand tonnes)]. Global fish importation increased by 154.39 % from 1990 to 2021, however, exportation

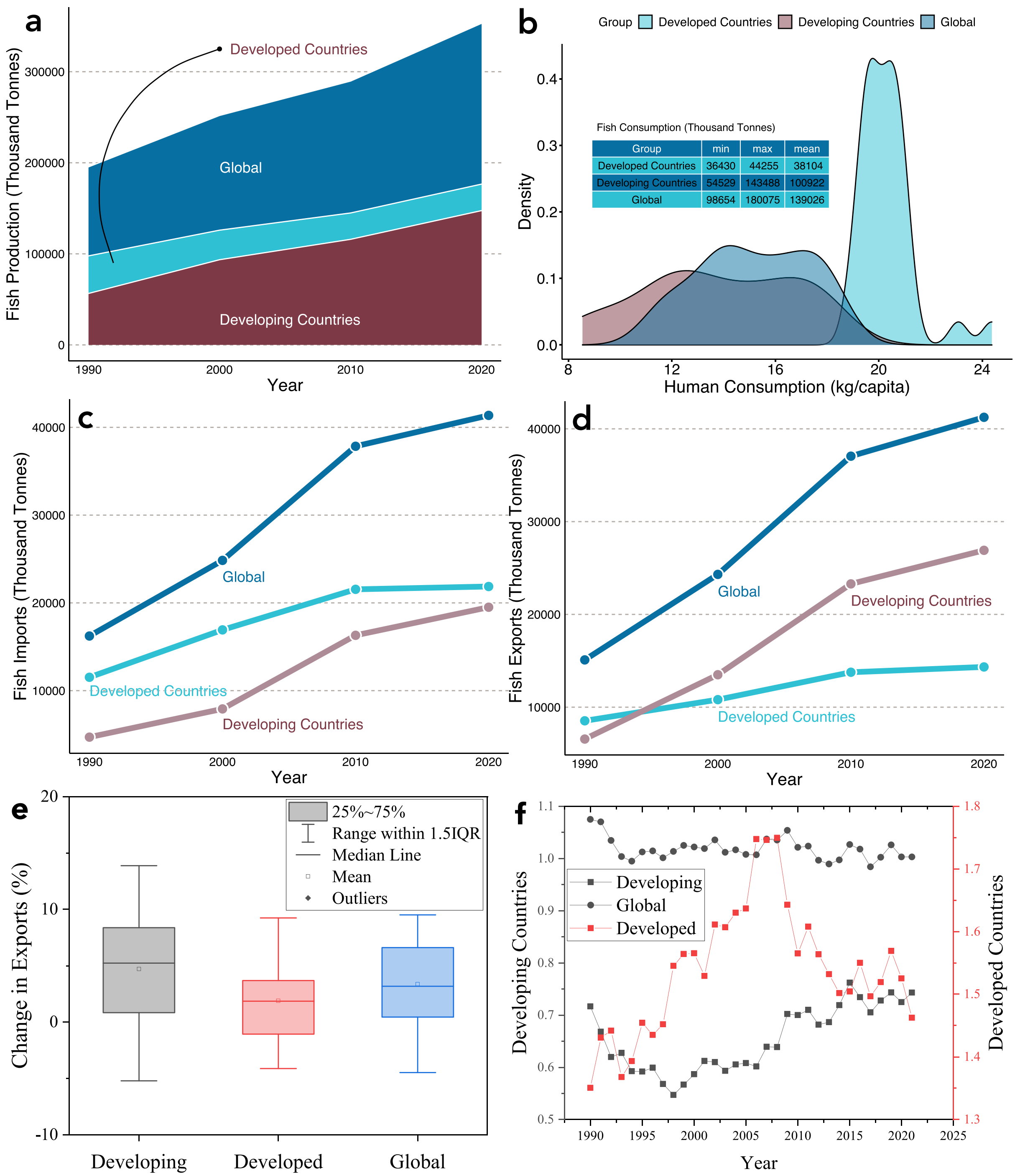

Fig. 1. Trends of fish distribution & trade. (a) Production [Thousand Tonnes] (b) Human Consumption [kg/capita] (c) Imports [Thousand Tonnes] (d) Exports [Thousand Tonnes] (e) Change in Exports [%] (f) Ratio of Imports:Exports. Panel a, average changes in production are 3.28 % (Developing), −1.02 % (Developed) & 2.02 % (Global). Panel b, average changes in human consumption are 2.37 % (Developing), −0.77 % (Developed) & 1.30 % (Global). Panel c, average changes in imports are 4.82 % (Developing), 2.12 % (Developed) & 3.11 % (Global). Panel d-e, average changes in exports are 4.70 % (Developing), 1.88 % (Developed) & 3.54 % (Global). Panel f, average ratios of intensities [imports:exports] are 0.65 (Developing), 1.54 (Developed) & 1.02 (Global).

grew by 172.63 % within the same period (Fig. 1c–d). The top 10 fish importers in 2021, representing 50.61 % of global importation include the US (5446 thousand tonnes, indicating 20.45 % of global fish imports), China, Japan, Thailand, Korea, the UK, Egypt, Nigeria, Russia, and Malaysia (Supplementary Table 4). Imports in developing countries grew by 315.24 % (from 1990 to 2021) compared to 88.66 % in developed economies. This is consistent with the yearly average change in imports in developing (4.82 %) and developed (2.12 %) countries (Supplementary Fig. 1a). The top 10 fish exporters in 2021 comprise China (6907 thousand tonnes, indicating 23.21 % of global fish exports), Vietnam, Russia, Norway, Chile, Thailand, the US, Indonesia, the UK, and Canada (Supplementary Table 5). These countries account for 58.02 % of total global fish export. Fish export increased by 300.51 % (from 1990 to 2021) in developing countries compared to 74.23 % in developed countries, corroborating the mean annual changes in exports by 4.82 % and 2.12 %, respectively (Fig. 1e). While fish import in developed countries outweighs export by 60.75 %, fish export in contrast exceeds import in developing economies by 59.85 %. Thus, the ratio of fish imports to exports is 1.54 and 0.65 in developed and developing economies, respectively (Fig. 1f).

3.2. Changes in fish distribution

The global distribution was generated using either the raw data or normalized mean samples from the panel dataset while controlling for periods across economies. The top 10 hotspots with high mean annual fish footprint (0.41–2.16 gha/person) include Norway, Belize, Solomon Islands, Denmark, Papua New Guinea, Chile, Fiji, South Korea, Japan, and United Arab Emirates. In contrast, the top 10 economies with low mean annual fish footprint (i.e., 0.001–0.005 gha/person) comprise Afghanistan, Ethiopia, Tajikistan, Sudan, Nepal, Uzbekistan, Mongolia, Somalia, Rwanda, and South Sudan (Fig. 2a). These economies have the highest or lowest mean of maximum harvestable fishing with production from various species (Teorell et al., 2021). Global economies with high population-weighted fishing biocapacity include the Bahamas, Suriname, Guyana, Australia, Canada, Qatar, Estonia, Norway, Guinea-Bissau, and Sweden. Yet, Central African Republic, Lesotho, South Sudan, Afghanistan, Serbia & Montenegro, Luxembourg, Niger, Czech Republic, Slovakia, and Iraq have the lowest mean annual fishing biocapacity (Fig. 2b). The high (low) ranked countries represent high (low) regenerating tendencies of the fish ecosystem to meet demands. Countries with increased levels of overexploited stocks include Bangladesh, Yemen, Vietnam, Comoros, Sierra Leone, Libya, Dominican Republic, Estonia, Madagascar, and Oman. On the contrary, Portugal, Italy, El Salvador, Denmark, Japan, Jamaica, Barbados, Canada, Spain, and Panama have the lowest average share of fish catches from collapsed stocks (Fig. 2c). The status of fish stock is an important environmental performance indicator that assesses how fishing practices increase stock overexploitation, leading to smaller fish catches. We further estimated the ecological status of nations using both fish footprint and biocapacity over time. Using the mean score of ecological status, we classified countries under ecological reserve (i.e., the top 10 countries include Bahamas, Suriname, Guyana, Australia, Canada, Qatar, Estonia, Guinea Bissau, Sweden, and Gabon) and ecological deficit (i.e., top 10 economies comprise Belize, Portugal, Japan, Spain, Barbados, Singapore, Solomon Islands, Switzerland, Philippines, and France). The ecological reserve herein identifies economies with fishing biocapacity outweighing fish footprint whereas ecological deficit classifies countries with fish footprint exceeding fishing biocapacity (Fig. 2d).

3.3. Global fish price volatility

Using the estimated ratio of returns, we examined the effect of fish price volatility on fish production, consumption, and trade in line with SDG 2(c). The shift estimation was derived using cross-sectional time series operators that account for both first-difference and historical effects across income classifications (see Empirical analysis). We observe a strong positive relationship ($R^2 = 0.72$–0.81) between global fish price returns and global production, consumption, imports, and exports (Supplementary Fig. 2). However, the decomposition of fish distribution by income classifications shows otherwise. The average price intensities against fish distribution are positive in developing countries but negative in developed economies. The average rate of change in global fish prices increases production and consumption by 105–107 % in developing countries but declines by 5–16 % in developed economies (Supplementary Fig. 3a–b). The average price intensities stimulate fish import and export by 79–99 % in developing countries and 20–43 % in developed countries (Supplementary Fig. 3c–d). These scenarios are consistent with historical trends and demonstrate possible price returns embodied in fish production, consumption, imports, and exports, especially in developing economies.

We further examined the effect of global fish price returns on fish distribution dynamics across economies using the bias-corrected cross-wavelet power technique (Veleda et al., 2012). Using the bivariate

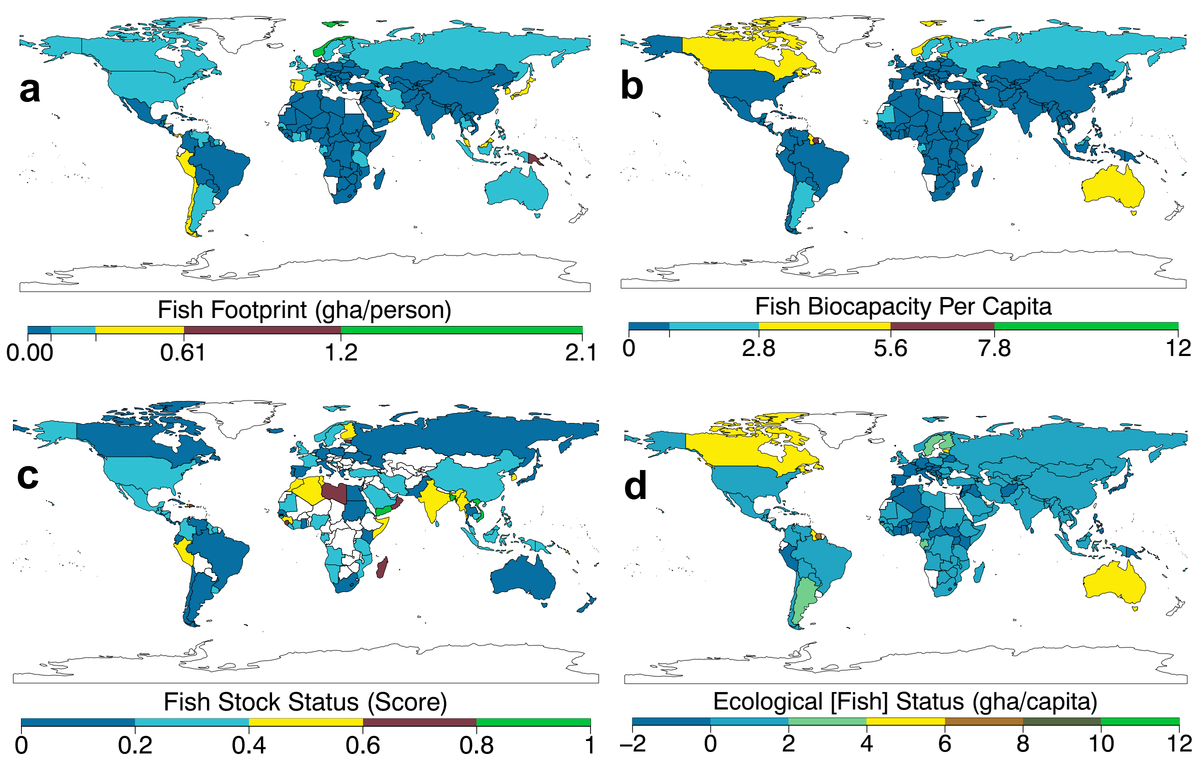

Fig. 2. Global mean distribution. (a) fish footprint [gha/person] (b) fish biocapacity per capita (c) fish stock status [score] (d) ecological fish status [score]. Panel a-b shows the generated mean samples from the cross-sectional time series dataset while controlling for time periods across economies. Panel c is the normalized [0,1] mean samples from 1995 to 2020. Panel d, ecological fish status was calculated by subtracting fish footprint consumption from fish biocapacity to classify economies under either fishery reserve (112 of 161 economies) or fishery deficit (49 of 161 economies).

signals, the time-varying spectral characteristics can show the link (phase relationship) between variables, thus, validating causality. The wavelet power spectrum emanates from the bivariate wavelet analysis of nonstationary series with short-lived signals containing time-frequency localization (see Model estimation).

The wavelet power spectrum shows weak relationships between fish distribution and trade against global fish price but statistically significant periodicity from 1990 to 2000 and 2009–2021 at the scale of 5.7–9.0. In both developing and global scenarios, we observe strong statistical phase relationships between fish distribution or trade and fish price from 2001 to 2008 (Fig. 3, Supplementary Fig. 4). However, the periodicity extends for exports and fish price nexus from 2001 to 2015 in both developing and global scenarios (Fig. 3j, k). The seeming similarity between the power spectrum of both developing and global scenarios demonstrates the dominance of fish distribution and trade dynamics of developing economies. The power spectrum of the wavelet analysis shows the relationship between global fish price and fish distribution & trade in developed economies is largely non-significant. Yet, the import-fish price nexus is the only strong statistical relationship observed in developed economies spanning 2006–2019. The upward movement of the arrows shows global fish prices drive fish importation in developed economies (Fig. 3h). We observe the non-significant relationship between global fish price returns and human fish consumption in all income classifications across the annual time spectrum (Supplementary Fig. 5).

3.4. Changes & drivers

The average change in marine trophic level is relatively low in high-income countries, especially in countries within the North Atlantic region but insignificantly different when compared with other income groups (Fig. 4a). This somewhat corroborates studies that report a historical decline in trophic levels, specifically in the North Atlantic region (Essington et al., 2006; Paiva et al., 2013). The top 10 countries with improved trophic levels comprise Iraq, Romania, Ecuador, Samoa, Iceland, Togo, Tonga, Tanzania, Dominica, and Ghana (i.e., mean annual increase of 0.59–1.48 %). Economies with a relatively high decline in mean trophic levels (i.e., an annual decrease of 0.42–1.23 %) include Montenegro, Eritrea, Cameroon, Chile, Benin, Singapore, Guyana, Argentina, Mauritania, and Croatia (Supplementary Fig. 6). The mean annual change in temperature is significantly higher in high- ($P < 0.01$) and upper-middle-income ($P < 0.05$) economies than in low- and lower-middle-income economies (Fig. 4b). Top global economies with increasing annual temperatures (i.e., a mean annual increase of 0.59–0.92 %) include Montenegro, Mongolia, Switzerland, Kyrgyzstan, Bosnia & Herzegovina, Serbia, North Macedonia, Austria, Romania, and the Slovak Republic. Contrary, economies with declining annual temperatures (i.e., mean annual decrease of 0.01–0.10 %) comprise Russia, Niger, Suriname, Papua New Guinea, Bolivia, Zambia, Zimbabwe, Chad, Nigeria, and Cameroon (Supplementary Fig. 7). This positive (negative) change in average annual temperature is indicative of rising (decreasing) temperatures in developed and emerging economies. Thus, while warm countries are becoming warmer, cold regions are becoming colder. Interestingly, we find evidence of increased wealth with a decline in mean temperatures and reduced income with rising levels of average temperatures (Supplementary Fig. 8), corroborating existing literature (Burke et al., 2015). The global levels of anthropogenic GHG emissions across income groups are achieving convergence—as we observe relatively high mean change in emissions in upper-middle-income economies but statistically insignificant from other income groups (Supplementary Fig. 9). The top 10 countries with positive change (i.e., mean annual increase of 4.02–13.6 %) in emissions are within the high-income or upper-middle-income classification namely—Australia, Bosnia & Herzegovina, Barbados, Saint Kitts & Nevis, Grenada, Maldives, Cabo Verde, Trinidad & Tobago, Seychelles, and China. Historically, anthropogenic emissions have declined by 2.2–4.4 % in Gabon, North Korea, Syria, Cameroon, Nigeria, Ukraine, Libya, Denmark, the United Kingdom, and United Arab Emirates (Fig. 4c). The estimated pairwise correlation with significant coefficients at $P < 0.05$ shows a negative correlation (i.e., $\rho = 0.16$–0.54) between sampled series (i.e., climate change vulnerability, ruralization, and average temperature) and fish footprint. However, a significant ($P < 0.05$) positive correlation (i.e., $\rho = 0.03$–0.61) is observed between sampled regressors (i.e., marine trophic level, urbanization, precipitation, fossil fuels, FDI, GHG emissions, energy use, HDI, and income level) and fish footprint (Fig. 4d). Using statistical techniques, the precursory assessment of temporal trends and data characteristics envisions the empirical analysis of sampled indicators.

3.5. Drivers of fish footprint

We used a machine learning-derived panel fixed effects estimator that controls nonlinearity, unobserved temporal effects, and time-invariant country-specific fixed effects (time-invariant heterogeneity) to investigate the global drivers of fish footprint (see Model estimation). Our empirical estimation lacking strict parametric assumptions reduces panel misspecification bias (i.e., we used orthogonal variables to improve numerical precision of panel estimations) although improving predictability (we achieved a predictive power of 93–99 %) and statistical inferences (robust p-values for both point estimates and quantiles). Our empirical model shows a significant positive ($p < 0.05$) lag-dependent variable (fish footprint$_{t-1}$), which demonstrates the persistent effects of fish footprint, which may be driven by historical consumption patterns (Fig. 5). Due to this tendency, fish footprint increases historically by at least 0.35 % across economies, regardless of unobserved specificities. Growth in marine trophic levels typically in developing economies implies a decline in fishing pressures, however, its fish stocks become a source of exploitation to meet demands in developed countries, thus, exacerbating the global fish footprint in long term by 0.27 %. This scenario corroborates the temporal trends of fish export in Fig. 1d.

Assessing the demographic dynamics of consumption patterns confirms the mitigating effects of ruralization and aggravating effects of urbanization on fish footprint. While ruralization declines fish footprint by 0.01 %, urbanization intensifies fish footprint by 0.02 %. Over half of the global population is reported to live in urbanized areas (Steinberger et al., 2012), which may lead to purchasing economies of scale—a fish cost advantage over the rural folks, hence, increasing consumption patterns. Human development increases fish footprint by 0.28 % due to improved standard of living, knowledge, and healthy lifestyle. Consistent with studies that report strong impact of energy on growth in production and consumption (Steinberger et al., 2012), we observe both energy consumption and persistent levels of fossil fuels significantly ($p < 0.05$) drive fish footprint by nearly 0.03–0.07 %. We included GHG emissions as a proxy indicator for climate change effects on fish footprint. We observe climate change has both direct and indirect impacts on fish footprint (i.e., increasing by 0.03 %) by influencing patterns of fish migration, the abundance of fish stock, regional-specific species, and mortality rates (Brander, 2010; OECD, 2011). We find climate change vulnerability—a function of climate exposure and adaptive capacity—to decline fish footprint by 0.40 %. The threat of climate change vulnerability to biodiversity triggers environmental consciousness to achieve sustainable production and consumption, thus, reducing threatened marine systems including the historical fish footprint using adaptation and climate-resilient options for resource management (Smith et al., 2001). Increased level of precipitation declines fish footprint by 0.02 % through the development of connectivity (through migration) between particular fish habitats (Shaw, 2016). Changes in precipitation patterns alter stream flows affecting organisms in the marine ecosystem.

We observe a diminishing effect of FDI, temperature, income level, and time trends on fish footprint estimated using the expression $x^{*} =$

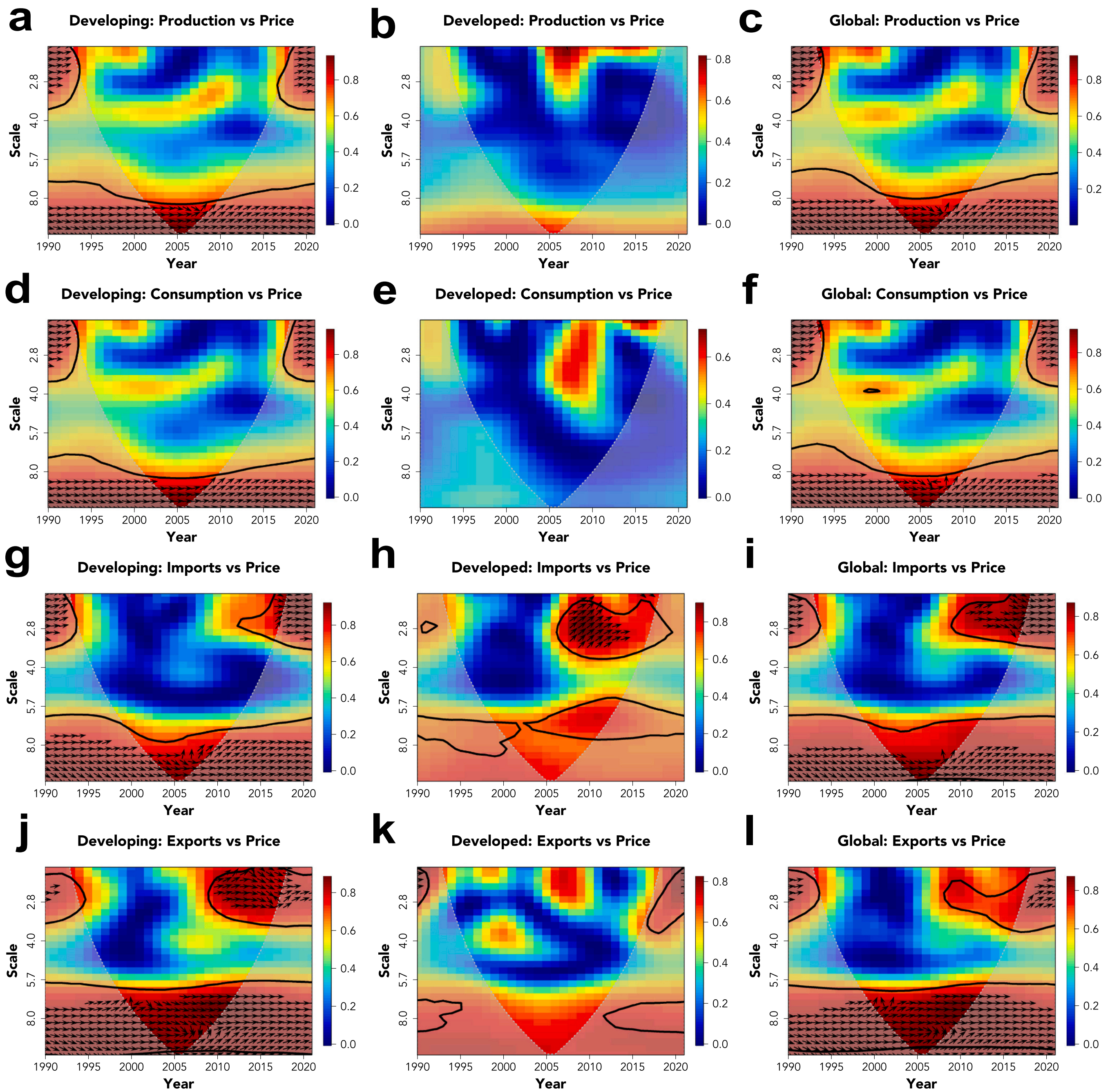

Fig. 3. Wavelet spectrum showing the effect of global fish price on fish distribution dynamics across economies. (a) Developing: Production vs. global fish price (b) Developed: Production vs. global fish price (c) Global: Production vs. global fish price (d) Developing: Consumption vs. global fish price (e) Developed: Consumption vs. global fish price (f) Global: Consumption vs. global fish price (g) Developing: fish import vs. global fish price (h) Developed: fish import vs. global fish price (i) Global: fish import vs. global fish price (j) Developing: fish export vs. global fish price (k) Developed: fish export vs. global fish price (l) Global: fish export vs. global fish price. The wavelet coherence was estimated using the bias-corrected cross-wavelet power technique expounded in Veleda et al. The horizontal axis shows the time periods whereas the vertical axis shows the scale (a lower scale shows high frequencies and vice versa). The dark red-colored regions signify the high inter-relationship between bivariate series whereas the dark blue-colored regions denote lower dependency between bivariate series. However, the dark blue-colored regions outside the area of significance depict the independence of time and frequencies from the bivariate series. The unshaded grey transparent layer with dotted lines represents the cone of influence (COI) demarcating regions not induced by edge effects. The shaded grey transparent layer of the COI is the region with suspected edge effects. The black-solid line denotes statistically significant ($P < 0.05$) levels of wavelet coherence computed from 2000 Monte Carlo randomizations. The phase plot shows black-colored arrows pointing right (implies both x & y variables are in phase), left (shows both x & y series are in anti-phase), upward (infers y leads x by $\pi/2$), and downward (infers x leads y by $\pi/2$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

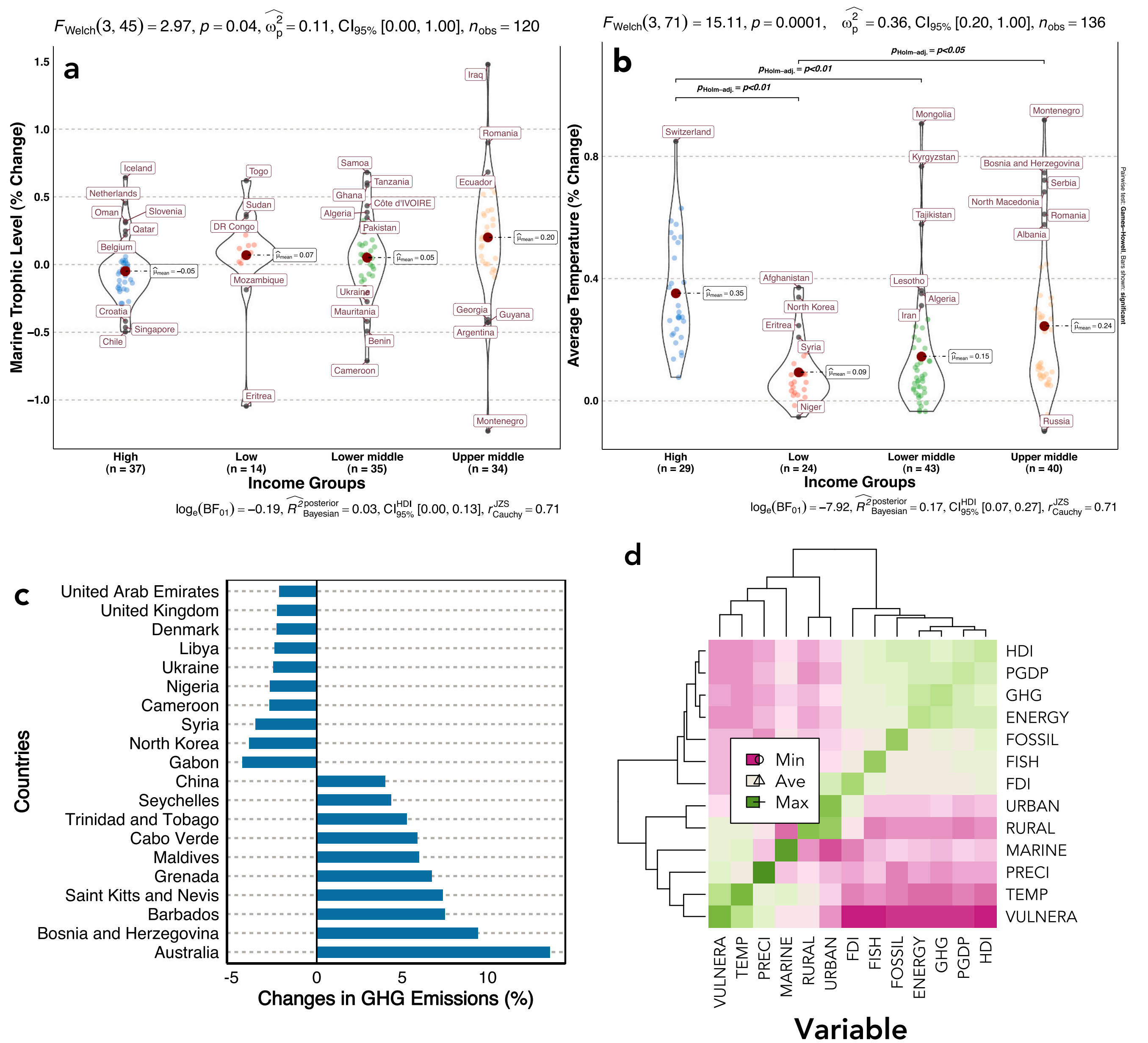

Fig. 4. Statistical distribution of variables. (a) Changes in Marine trophic level (b) Changes in average annual temperature (c) Changes in GHG emissions (d) Correlation among variables. Panel a–b was generated using the mean shift estimation samples from the cross-sectional time series dataset that controlled for time periods across economies. Panel c denotes the shift estimation derived using panel data operators that capture both first-difference and historical effects. Panel d was developed using the estimated pairwise correlation with coefficients significant at *P*-value < 0.05. The dark pink-colored square represents a strong negative correlation whereas the dark green-colored square signifies a strong positive correlation. Legend: HDI = human development index, VULNERA = Climate change vulnerability, ENERGY = Energy use, FDI = Foreign direct investments, PGDP = Income level, URBAN=Urbanization, RURAL = Ruralization, GHG = Greenhouse gas emissions, FOSSIL = Fossil fuel energy utilization, MARINE = Marine trophic index, PRECI = Average annual precipitation, TEMP = Average annual temperature, and FISH=Fish footprint. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$\widehat{\beta}_1 X/(-2\widehat{\beta}_2 X^2)$. The initial rise in FDI, temperature, income level, and time trends have positive effects on fish footprint but the effect becomes zero when FDI, temperature, income level, and time trends increase by 1.85 %, 0.10 %, 0.52 %, and 1 %, respectively, subsequently declining fish footprint. This highlights a parabolic shape of the fish footprint-income nexus, validating the F^2KC hypothesis across income classifications illustrated in Fig. 6a. Further observation shows fish footprint increases along income groups in the order: high-income > upper-middle-income > lower-middle-income > low-income countries (Fig. 6a). The country-specific effects show time-invariant between-country unmeasurable variations and unobserved specificities including inter alia gender, race, culture, and religion that either stimulate (positive effects) or slow down (negative effects) fish footprint (Fig. 6b). For example, the effect of unobserved characteristics has the highest positive effects in Norway and the lowest negative effects in Angola (all coefficients across countries are significant at $p < 0.01$ except for 32 economies, see Supplementary Table 6). External funding through foreign investments has resource efficiency effects that limit fish footprint. An increase in temperature increases water temperature, leading to changes in the distribution of species (Barange et al., 2018). The role of time trends shows changes in technology and innovation have long-term mitigating effects on fish footprint.

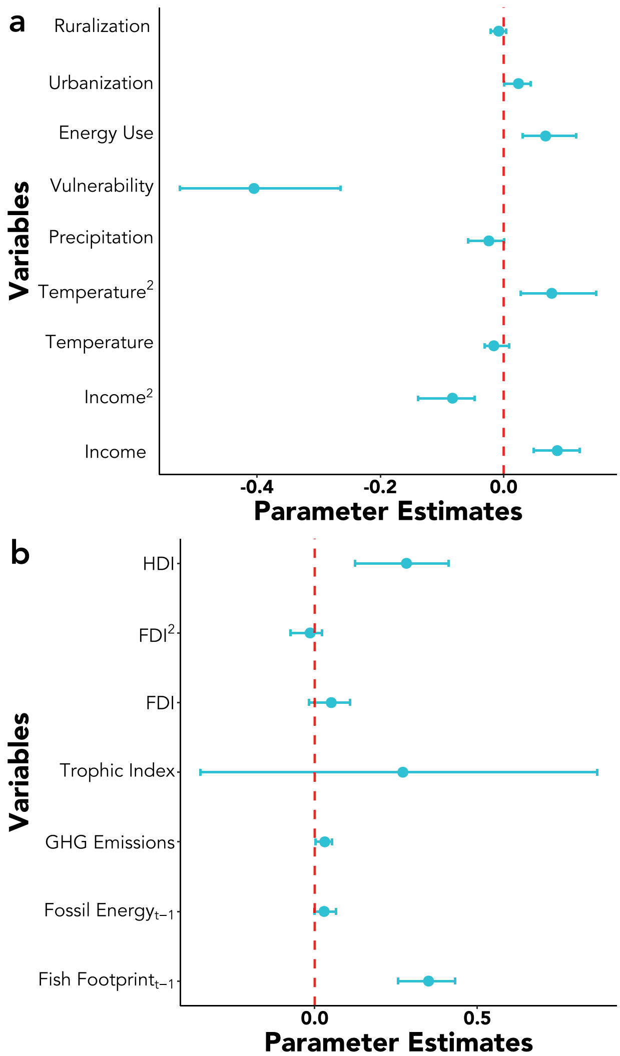

Fig. 5. Estimated parameters showing the drivers of fish footprint. (a) Model 1 (b) Model 2. The forest plots only show significant parameters estimated using the KRLS machine learning technique. The light-blue horizontal error bar (—) represents the 95 % confidence interval whereas the solid-dot (•) denotes robust coefficients statistically significant at *P-value* <0.05 for all models. Model 1: $R^2 = 0.951$, Eff. Df = 101.600, Tolerance = 0.724, Lambda = 0.279, Looloss = 61.66, Sigma = 58, Obs = 724, Trend = 0.063 (*P-value* < 0.01), Trend^2 = −0.032 (P-value < 0.05), and Country-specific effects = Yes. Model 2: $R^2 = 0.992$, Eff. Df = 548.700, Tolerance = 0.835, Lambda = 0.137, Looloss = 81.89, Sigma = 82, Obs = 835, Country-specific effects = Yes, and Yearly-fixed effects = Yes. Both models were validated using the panel quantile regression while controlling for heterogeneous effects across economies. The diminishing effect of FDI, temperature, and income level are estimated using the expression: $x^* = \widehat{\beta}_1 X / (-2\widehat{\beta}_2 X^2)$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Discussion & conclusion

In this study, we have documented empirical evidence of historical changes in fish footprint characterized by increased fish production and consumption (SDG 12). The existing research identifies high human dependence on the marine ecosystem (to provide coastal protection, cultural values, employment, and food) specifically in dense coastal populations in developing economies (Africa, Asia, and small island nations) (Selig et al., 2019). Regions with strong human dependence on marine resources coincide with social-ecological hotspots with high climate change vulnerability, highlighting the significance of integrating human dependence into marine conservation and management policies (Sarkodie et al., 2022; Selig et al., 2019).

The persistent levels of fish footprint show the effects of behavioral and lifestyle changes that affect global demand for fish resources and subsequently, fish consumption patterns. Studies associate the strong relationship between fish consumption patterns, and behavioral and lifestyle changes to health-conscious dietary choices (Oken et al., 2008), cultural and societal influences (Cornelsen et al., 2015), and concerns with sustainability and environmental awareness (De Boer et al., 2014). The increased fish consumption per capita in developed economies stimulates fish demand from developing countries through imports. With limited fishing grounds, viz. ecological deficit, and sustainable fish management, many economies meet their demand by importing fish resources, which may facilitate fish footprint-embodied in exports, especially when fish stock is overexploited using unsustainable fish practices. Similar results of global fishing inequality showing disparities in fisheries management are reported by Klein et al. (2022). The study showed that countries with weak fisheries management systems (i.e., lack the institutional quality to enforce sustainable fishing practices) face fishing pressure and are more likely to engage in unsustainable fishing practices leading to habitat degradation and overfishing—with long-term negative impacts on marine biodiversity (Klein et al., 2022).

Achieving a nutritious and healthy lifestyle (SDG 3) involves increased availability, accessibility, and affordability of healthy options including fish and fish products. Yet, these three pillars of development appear dwarfed, endangering long-term food security, especially in low-income economies. Golden et al. (2016) showed that developing economies rely heavily on fish as a primary source of nutrition (essential fatty acids, high-quality protein, vitamins, and minerals) and income, hence, a decline in fish stocks overly affects (i.e., leading to nutritional deficiencies and increased vulnerability to health outcomes) vulnerable populations, especially in developing countries. This infers that the alarming decline of global fish stocks and disruptions in fishing patterns have long-term effects on human health and food security while reducing income opportunities and exacerbating poverty (Blasiak et al., 2017).

We showed that global price volatility has a significant effect on fish production, consumption, import, and export in developing economies but is insignificant in developed countries. A similar study on income and price interactions (Cornelsen et al., 2015) corroborated our findings, arguing that the price elasticity of food demand is higher for developing economies, specifically lower-income populations compared to high-income economies. This implies that changes in price have a relatively greater effect on food consumption patterns in developing countries, specifically lower-income groups. The advantage of fish purchasing power in developed nations regardless of global price volatility explains why among other factors—fish stock collapse and small catches are highly prevalent in developing countries, especially low-income nations.

We found strong effects of affluence, urbanization, and human development on fish footprint, especially in developed economies. Wealthy countries consume more fish to ensure a healthy lifestyle that declines diet-attributed morbidity and mortality whereas poor economies consume more fish resources as an alternative to expensive meat and meat products (Hirvonen et al., 2020).

The empirical assessment of drivers and trends of fish footprint offers policy implications useful as mitigation options. The over-reliance on fish exploitation to end hunger (SDG 2) in food-insecure regions will only have a short-term impact on sustenance but will intensify both ecological deficits (because of fish depletion) and fish footprint in the long term. However, investments in the restoration of the marine ecosystem including fish resources (SDG 14) provide lasting co-benefits of reducing species extinction, providing economic opportunities (employment), and improving food security (Singh et al., 2018).

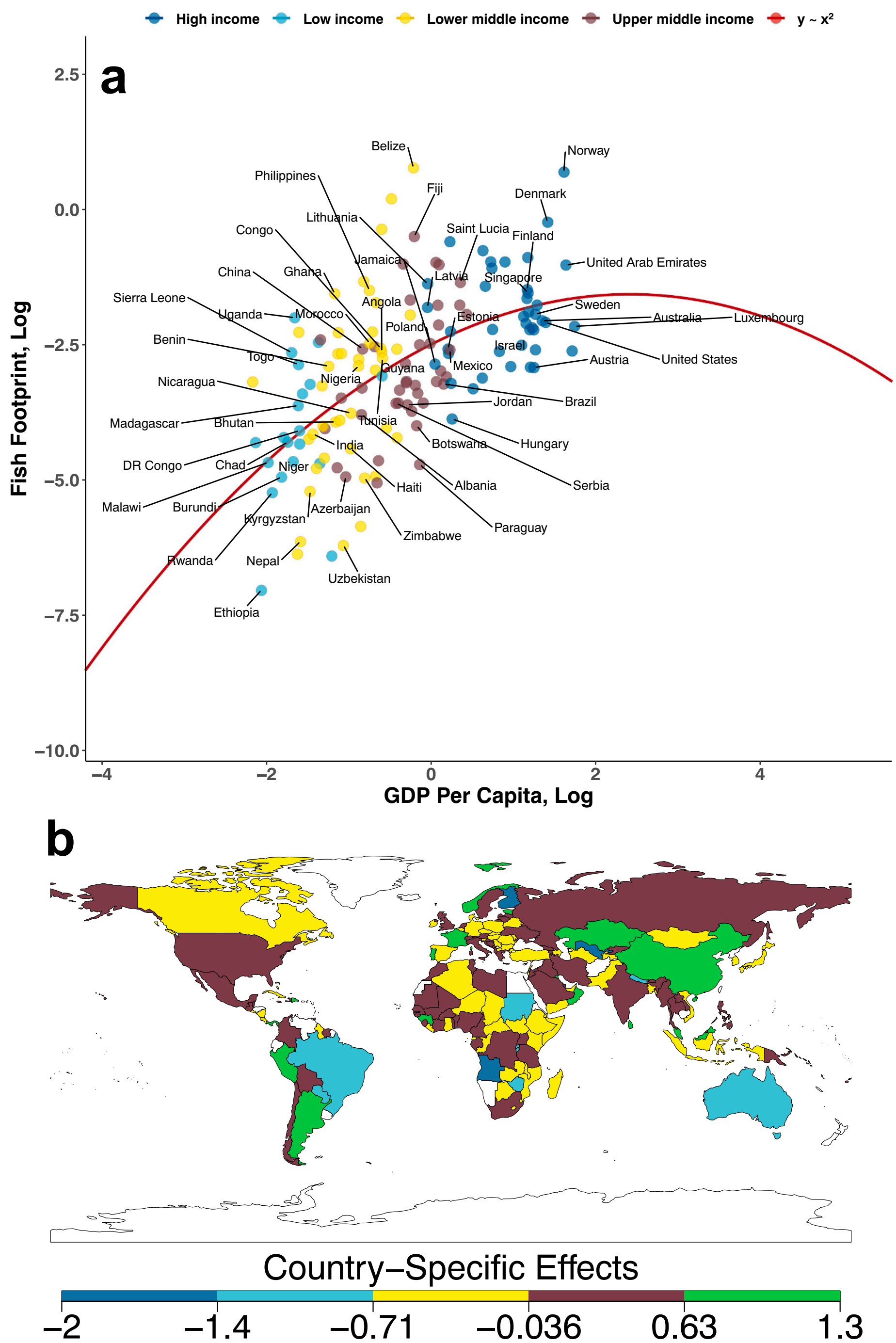

Fig. 6. Parameter Estimates showing. (a) the fish-based footprint Kuznets curve across economies (b) Country-specific effects of fish footprint embodied in income. Panel a depicts the visualization of the fish footprint Kuznets curve (F^2KC) hypothesis generated using the mean log of fish footprint and mean log of income level while accounting for income groups (high-, upper-middle-, lower-middle-, & low-income). Panel b shows the country-specific fixed effect generated after validating the F^2KC hypothesis while accounting for income convergence (i.e., this is the third model estimated with only income, quadratic of income, time trends, and quadratic of time trends by economies, yet controlling for unobserved and time-invariant country-specific fixed effects that account for time-invariant heterogeneity affecting fish footprint).

CRediT authorship contribution statement

S.A.S: Conceptualization, Formal analysis, Methodology, Software, Validation; Visualization, Writing – review & editing. P.A.O: Writing the original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data used for the empirical analysis are publicly available, see Table 1 for details.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.marpolbul.2023.115369.

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