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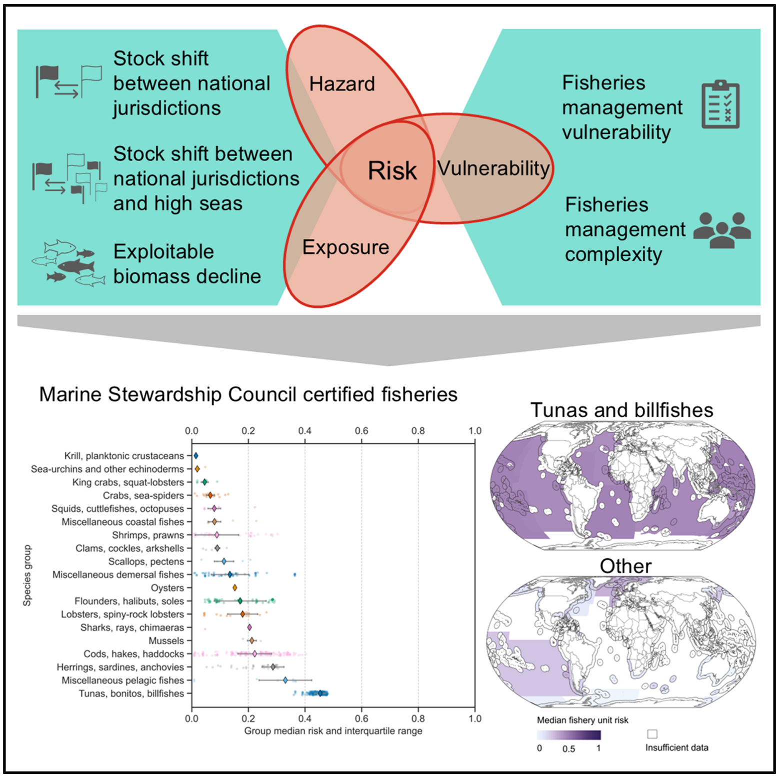
Climate change risks to future sustainable fishing using global seafood ecolabel data

Graphical abstract



Highlights

- Exposure to climate change effects creates risk to fisheries' management globally
- Opportunities to evolve management could reduce vulnerability, especially for tunas
- More efficient cooperation in managing multinational stocks is key to reduce risk

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In brief

This study combines projected changes in fish stock distributions and marine biomass with fishery vulnerability indicators to conduct a large-scale assessment of climate change risk to sustainable management of marine fisheries. Results highlight that efficient multinational cooperation in widely distributed large pelagic species will be particularly important to mitigate impacts.

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Climate change risks to future sustainable fishing using global seafood ecolabel data

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SCIENCE FOR SOCIETY Climate change is impacting sustainable use of the world's natural resources, including marine fisheries, which are a critical source of food and livelihoods. Climate change-driven shifts in fish population distributions and declines in fish biomass are already affecting fishing opportunities, and these effects are expected to increase. Management systems may no longer be suitable for sustainable extraction under these new conditions, resulting in overfishing. Global patterns of fishery risk, incorporating management vulnerabilities, have been difficult to measure due to a lack of consistent, relevant information compiled on a global scale. We fill this gap by combining recently published climate projections with novel governance proxies to evaluate fishery risk across large spatial scales and diverse species groups. Our results help identify governance areas to be prioritized, such as multinational catch allocation agreements, to adapt to projected changes, mitigate risk, and sustain future seafood supplies and dependent communities.

SUMMARY

Marine fisheries are an important source of food and livelihoods globally. However, climate-induced changes in marine ecosystems are affecting fish populations and sustainable fishing opportunities. By combining datasets on climate-driven changes in population distribution and biomass with Marine Stewardship Council (MSC) seafood ecolabel program data, we conduct a large-scale risk analysis of fisheries under a high-emissions scenario by mid-century. Results show that fisheries targeting tuna and billfish face the highest relative risks of management disruption, due to high exposure to stock shifts and higher governance vulnerabilities, followed by small pelagic and demersal fisheries. We analyze a subset of global fisheries with high management performance (MSC-certified), suggesting risk may be higher among non-MSC-certified fisheries. These findings provide key insights into governance priorities across diverse fisheries under climate change. They underscore the need for international cooperation, regular management reviews, and effective monitoring to be prepared for climate impacts on marine resources.

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INTRODUCTION

Climate change is impacting the biodiversity and sustainable use of natural resources globally. In marine systems, changes in ocean temperatures, seasonality, and circulation are impacting habitats, altering populations' abundance, shifting species' distribution, and affecting food-web structure. These changes are already impacting sustainable fishing opportunities, threatening livelihoods and food security.[1–4] Phenomena such as stocks shifting out of historical fishing grounds and changes to food-web productivity are projected to increase, thereby increasing risks of fisheries-related conflict and unsustainable management.[5,6] Even fisheries considered to be well managed can face consequences from these changes,[7,8] as strategies that have historically facilitated a sustainable fishery may result in unsustainable outcomes under new conditions. Fisheries' risk of adverse outcomes will vary based on exposure to climate change effects, such as the extent of biomass decline and target stock distribution shifts, and management systems' vulnerability that includes the ability of management systems to efficiently identify, respond to, and cope with impacts.[5,6,9,10] These factors affecting risk have been challenging to evaluate across large spatial scales and diverse species groups.

Exposure to climate change challenges the effective and resilient management of stocks, which requires the full cooperation of all parties, including coastal states with potentially diverse systems and agendas. Under climate change, many fish and invertebrate stocks are projected to shift across exclusive economic zone (EEZ) boundaries beyond historical distributions, which is predicted to increase disagreements over catch allocations.[6,7,11,12] To ensure resilient management systems and avoid overfishing, management agreements, which may have historically been effective, will require adjustment, including agreements on catch allocation and rules that may govern future revisions to current allocations.[13,14] When stocks are distributed across multiple jurisdictional boundaries, successful agreements can be more challenging to achieve from having more parties involved in decisions, making full cooperation more difficult[7,15–17] and thus creating further vulnerabilities to climate change impacts. For example, allocation may be based on a country's historical catch development status or reliance on the fishery resource, but changes in fish biomass or distributional shifts, resulting in changes in abundance across jurisdictions, may necessitate reviewing these criteria and could result in difficult multi-country negotiations.[13,14,18] When a stock is distributed across multiple EEZs, the harvest strategies and access agreements for all countries involved can impact its sustainable harvest. In Northeast Atlantic pelagic fisheries, disputes over allocation stemming from stock distributional shifts could not to be efficiently resolved, which contributed to collective quotas and catches being higher than advised and fisheries of the stock no longer being considered sustainable.[19,20] Thus, as climate change progresses, sustainability of stocks will necessitate that management systems can cope efficiently and that all countries involved work together cooperatively.[7,15,21]

Even when parties are willing to cooperate or when there are a few parties involved, the fishery may face closure or depleted biomass when distributional shifts or biomass changes are not identified in time and management strategies are not quickly adapted.[22] For example, biomass decline of North Sea cod, partially attributed to climate change impacts,[23,24] meant that existing harvest strategies became inadequate.[25] The lack of an adequate management plan under the changed conditions then resulted in fisheries targeting North Sea cod to lose their Marine Stewardship Council (MSC) certification.[25]

Accordingly, the risk of future consequences from climate change effects will be influenced by the vulnerabilities of fisheries' management systems. As socio-ecological systems, the vulnerability of a fishery to climate change hazards varies depending on the context of the fishery,[9] and so measures ascertaining vulnerability are difficult to quantify globally. Certain attributes of management systems have been proposed as promoting the ability to identify and adapt to climate-induced changes, including regular re-evaluations of decision-making mechanisms, inclusive stakeholder consultation, and flexibility to respond rapidly.[9,26,27] At the same time, management structures should ensure regulations are effective through appropriate implementation and compliance and enforcement mechanisms. These attributes help to ensure that harvest strategies are effective and promote sustainable outcomes. However, it has been challenging to obtain comparable, systematically collected, fishery-level data on elements of fisheries management such as these.

The MSC is a seafood ecolabel program aimed at providing market recognition to products from wild-capture fisheries that meet its environmental sustainability requirements.[28,29] As of 2023, 16% of wild-caught marine landings were MSC-certified, with 66 countries selling MSC-labeled products to consumers[30] and more than 650 fisheries engaged in the program.[31] MSC-certified fishery assessments are conducted by independent, accredited, third-party auditors and are made publicly available for stakeholder comment.[32] Each fishery is scored against performance indicators within three overall principles of the fisheries standard[33] related to whether (1) the target stock is fished at sustainable levels, (2) habitats and ecosystems remain healthy, and (3) effective management systems are in place.[28] Each fishery is assessed and scored from 60 to 100 against criteria within each performance indicator, with higher scores indicating more comprehensive and demonstrably effective processes for sustainable outcomes.[28] If the fishery does not meet the minimum required score of 60 for all criteria of each performance indicator or a weighted average score of $\geq$80 for each principle, then it fails the assessment and cannot be certified.[33] These MSC fishery assessment reports systematically document the performance of assessed fisheries and their management systems. While MSC-certified fisheries are likely to perform better, on average, than a random sample of the world's fisheries, they include a diverse set of target species, gears, scales of operation, and geographic representation that can provide key insights into large-scale risk patterns under future climate scenarios.

Here, we use scores for the indicators assessed under Principle 3 of the standard. While scores under principles 1 and 2 reflect current practices in place, we selected Principle 3 scores as these capture the characteristics of governance systems and processes, which can all be associated to some degree with important attributes for reducing vulnerability to climate change.[9] Although the standard was not developed to specifically evaluate climate change vulnerability, Principle 3 scores that are informative of attributes that can be associated with climate-resilient fisheries[9] include the efficiency and effectiveness of decision-making processes and resolving issues and disputes, as well as the capability to update or create new regulations.[9] The detailed scoring guidance and training provided to auditors, as well as assurance systems surrounding certification, are intended to create a replicable scoring methodology for marine fisheries globally, even when applied to scoring qualitative aspects such as the level of stakeholder consultation or adequacy of dispute resolution.[34]

We combine multiple datasets on stock distributions, fisheries, climate change, and governance indicators to conduct a climate change risk evaluation of fisheries in the MSC program under a high greenhouse gas emissions scenario by mid-century (2050). Exposure, measured by the presence of fisheries in areas that could be adversely affected by these hazards,[30,35] and vulnerability, measured by the fishery management system's susceptibility and lack of capacity to respond to and recover from adverse impacts,[30,35] are evaluated to determine overall risk. We aim to identify large-scale patterns of risk of climate change disrupting sustainable fishery management because of potential conflicts over catch allocation or the reduction of exploitable biomass. We evaluate factors contributing to risk, including exposures to shifting distributions and biomass change, and potential vulnerabilities of management systems that could be addressed to mitigate future impacts. We identify fisheries targeting highly migratory tunas and billfishes, followed by those targeting small pelagic species, to be at higher risk than other fisheries evaluated, generally resulting from higher exposure and potential vulnerabilities from the challenges of complex multinational governance.

RESULTS

Risk estimate varies by target species group and geography

We estimated the risk of 661 fishery units—defined as the combination of the target stock, fishing method, and the vessels or operators pursing that stock—to climate change by mid-century (2050) under a high-emissions scenario, representative concentration pathway 8.5 (RCP8.5) or shared socioeconomic pathway 5-8.5 (SSP5-8.5). Risk is ranked on a scale from 0 (least risk) to 1 (most risk), and fishing units are grouped according to the International Standard Statistical Classification of Aquatic Animals and Plants (ISSCAAP).[36] Risk values tended to cluster in three groups: large pelagic fish, small pelagic and demersal fish, and invertebrate species groups. Fishery units targeting large highly migratory pelagic fishes (tunas and billfishes) had, on average, the highest estimated risk, with a median risk of 0.45 and interquartile range (IQR) from 0.43 to 0.46 (Figure 1). Most groups of small pelagic and demersal fishes, including gadids and flatfishes, had low to intermediate levels of risk (7 out of 8 of these groups had median risk between 0.13 and 0.33). Invertebrate species groups tended to have lower risk on average, compared with fish groups (8 out of 11 invertebrate groups had median risk between 0.01 and 0.11; Figure 1). Risk estimates for individual fishery units in the MSC program ranged from 0.0001 to 0.48, with median risk of 0.23 and an IQR from 0.09 to 0.36. Standard uncertainty for individual fishery unit risk estimates, resulting from Monte Carlo simulations, ranged from ±0.0003 to ±0.1116. We estimated that not accounting for covariances among indicators during these simulations results in underestimating risk by 2.2 percentage points (Figure S1).

Aggregating by EEZ(s) where fishery units operate, the highest-risk EEZs were those dominated by fishery units targeting tunas and billfishes, particularly in the Western Central Pacific (Figure S2). However, many equatorial regions lacked representation of fishery units targeting other species besides these large pelagic fishes (Figures S2and 2B). On average, fishery units targeting tunas and billfishes had similar risk across most areas of operation (Figures 2B and S2), in part because these areas are large. For example, fishery units operating in the Western Central Pacific often operated in multiple Pacific Islands EEZs and high seas regions, with the risk value applied to all grid cells. Further, because tuna and billfish stocks have large distributions, indicators calculated based on stock distribution (EEZ shift, high seas shift, exploitable biomass decline, and governance complexity) had uniform values for all fishery units targeting a stock. Aggregated risk tended to be higher in European countries than non-European countries for fishery units targeting non-tuna species groups (Figure S2).

Exposure and vulnerability indicators contributing to higher risk vary

The risk estimate for each fishery unit was calculated from five indicators of exposure and vulnerability (Figure 2). We compared fishery units targeting tunas and billfishes with those targeting other species, given that the former mainly occur in the high seas and are managed through multi-country Regional Fisheries Management Organizations (RFMOs) that operate differently from management structures and processes of EEZs. Fishery units targeting tunas and billfishes generally had higher values of all exposure and vulnerability indicators than fishery units targeting other species, leading to higher overall risk (Figure 2A). The discrepancy was particularly extreme in EEZ shift, high seas shift, and governance complexity indicators, where medians for tunas and billfishes were all 1 and for fishery units targeting other species were less than 0.75. Within each of these three indicators, at least 80% of fishery units targeting tunas and billfishes had a value of 1. For fishery units targeting other species, EEZ shift exposure had the highest median of all indicators at 0.74 (IQR 0 to 1). Most fishery units targeting other species with EEZ shift exposure $\geq$0.99 operated in the Northeast Atlantic Ocean, while a portion also had an EEZ shift $\geq$0.99 in the eastern Russian EEZ, western Canadian EEZ, and Chilean EEZ (Figure S3). Across all types of fisheries, median scores for exploitable biomass decline were the lowest of all exposures (median = 0.21 and IQR 0.14 to 0.30), while management vulnerability was the vulnerability indicator with the lowest median scores (median = 0.12 and IQR 0.08 to 0.15). Across all indicators and thus overall risk, the variance among fishery units tended to be greater for those targeting other species (Figure 2A).

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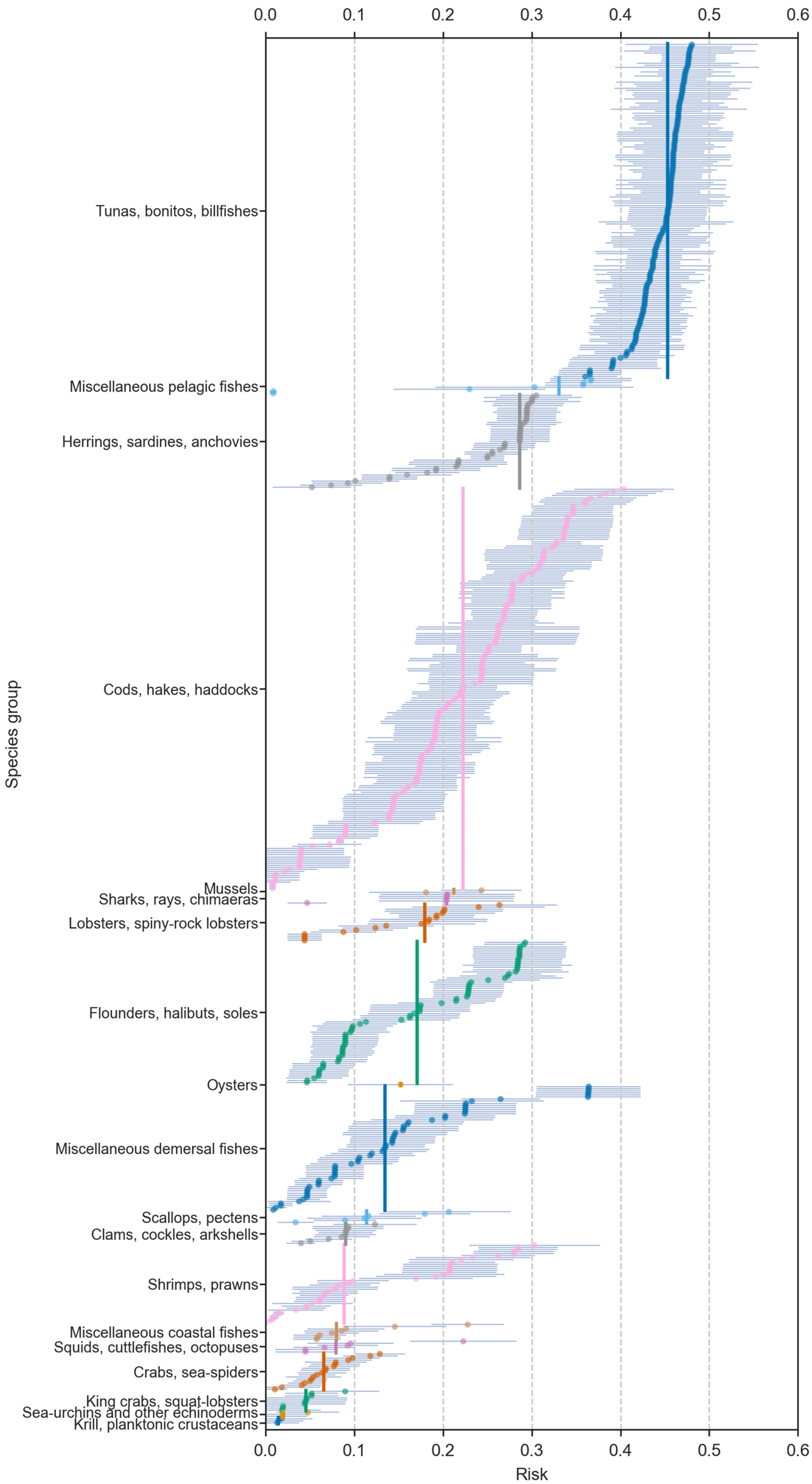

Figure 1. Risk estimate of individual fishery units, calculated as mean risk from Monte Carlo simulations

Error bars show standard uncertainties, measured by ±1 standard deviation across Monte Carlo simulations. Fishery units grouped by ISSCAAP species group (separated by color), with solid vertical lines showing group median risk. Possible risk values range from 0 to 1, but the highest observed risk was 0.48.

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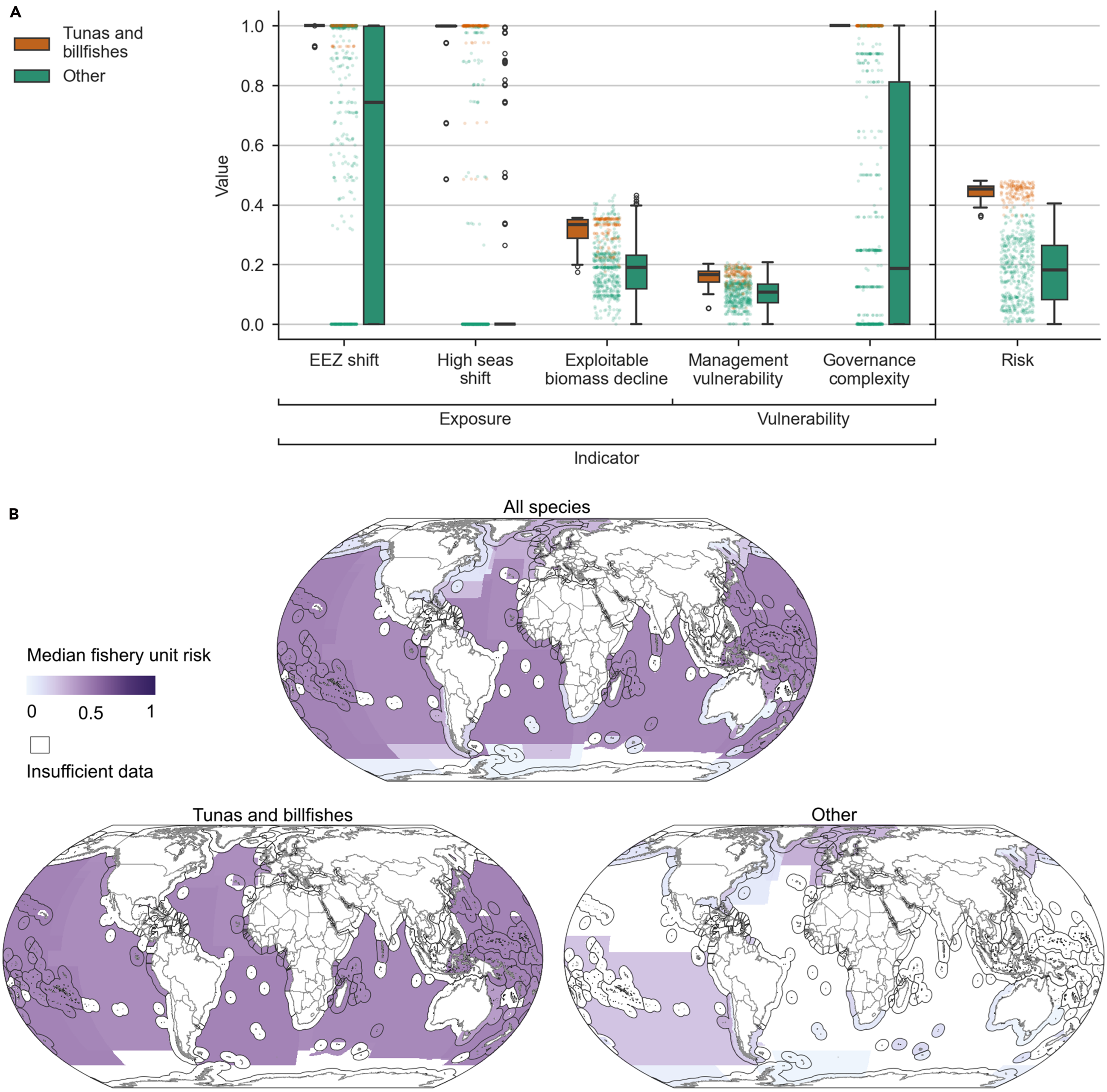

Figure 2. Exposure and vulnerability indicator values and overall risk values across fishery units

(A) Fishery unit exposure and vulnerability indicator values and overall risk, separated by fishery units targeting tuna and billfish species versus those targeting other species. Boxes show interquartile range (IQR) and bold lines show median. Whiskers show lowest datum within Q1 $-$ IQR $\times$ 1.5 and highest datum within Q3 + IQR $\times$ 1.5, while black open points show observations outside these fences. Colored points show values for individual fishery units.

(B) Global maps of median risk across all fishery units by 0.5° $\times$ 0.5° cell, showing EEZs for reference. Scale shows full range of possible risk values (0 = lowest risk, 1 = highest risk), but the highest observed risk across fishery units was 0.48.

Across all fishery units, the lowest exposure to declining exploitable biomass ($\leq$0.08) was observed for those targeting stocks toward the poles, particularly in the Barents Sea, northern Baltic Sea, Antarctic, Heard and McDonald Islands, Gulf of Maine, and Nova Scotian shelf (Figure S3). For fishery units targeting stocks other than tunas and billfishes, the highest exposure to declining exploitable biomass (0.35–0.43) was found among those targeting stocks in the Gulf of Alaska, Bering Sea, Aleutian Islands, Grand Banks, southeastern Australia, and New Zealand. Some of these fishery units also had moderate to high exposure to EEZ shift, but generally low exposure to high seas shift, and low vulnerability indicator values compensated, resulting in relatively lower risk (<0.26). Of these with higher exploitable biomass decline, the highest

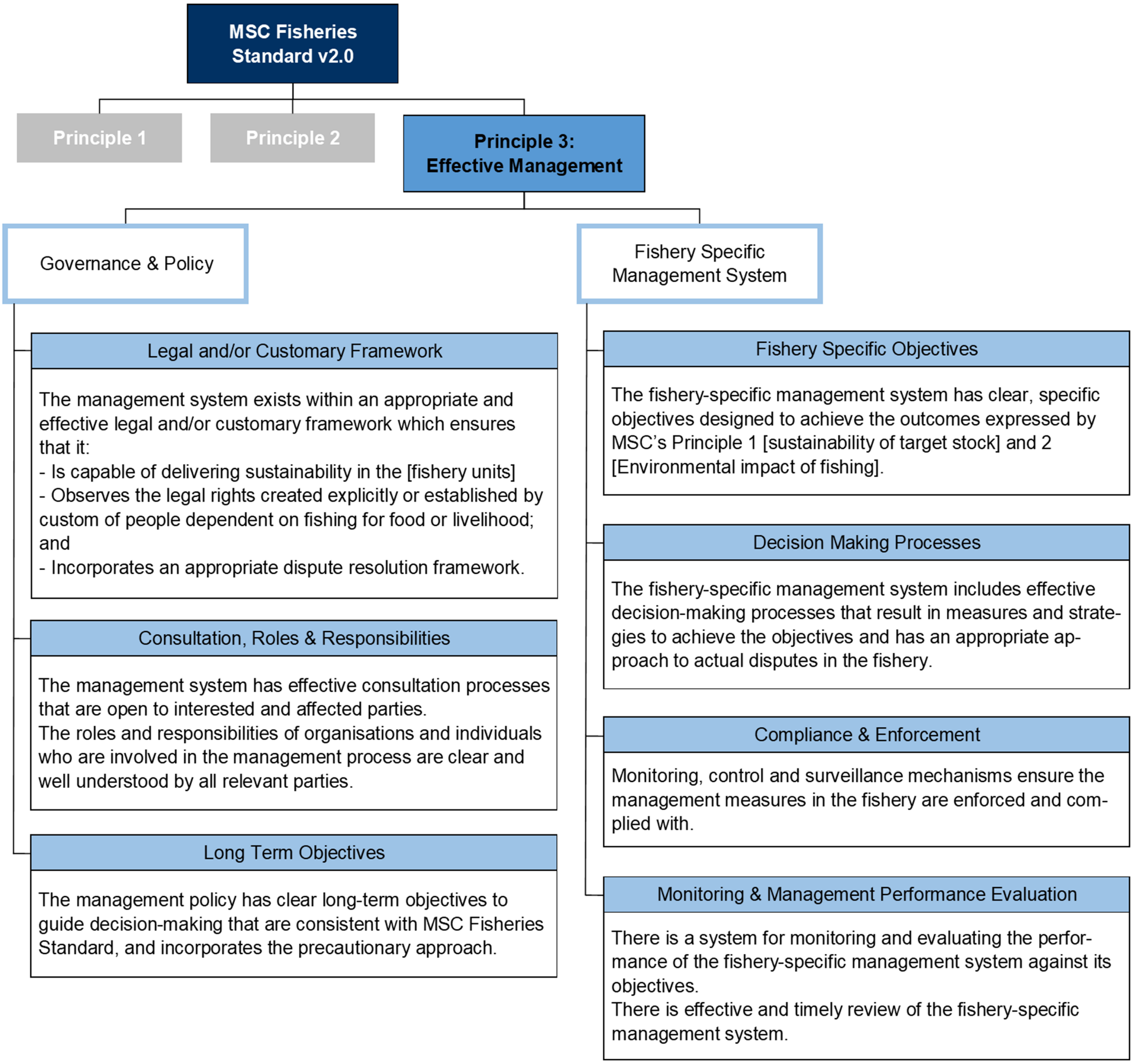

Figure 3. MSC fisheries standard 2.01 assessment criteria for Principle 3

Seven light blue filled boxes and accompanying black and white boxes describe the seven performance indicators scored within Principle 3 to assess the effectiveness of management systems. Adapted from the MSC fisheries standard v2.01.[28]

risk was for those targeting stocks in state waters of the Gulf of Alaska and Aleutian Islands (risk = 0.26) where high EEZ shift of 1 also contributed to higher exposure, and higher management vulnerability of 0.19 contributed to higher overall risk.

Management vulnerability ranged from 0.001 to 0.21. These overall low values, compared with those of other indicators, reflect that our sample consisted of only fisheries that met MSC requirements for Principle 3 scores and thus had at least some characteristics that could be associated with reducing vulnerability.

Underlying management vulnerabilities contribute to higher risk estimates

To better understand potential management vulnerabilities, we examined the seven governance performance indicators composing the MSC fisheries standard Principle 3 (Figures 3 and 4) and thus the management vulnerability indicator (Figure 2). Fishery units targeting tunas and billfishes generally scored lower (less favorably) in most performance indicators assessing management effectiveness (Figure 4B). For fishery units targeting other species, the lowest scores were generally in the monitoring and management performance evaluation

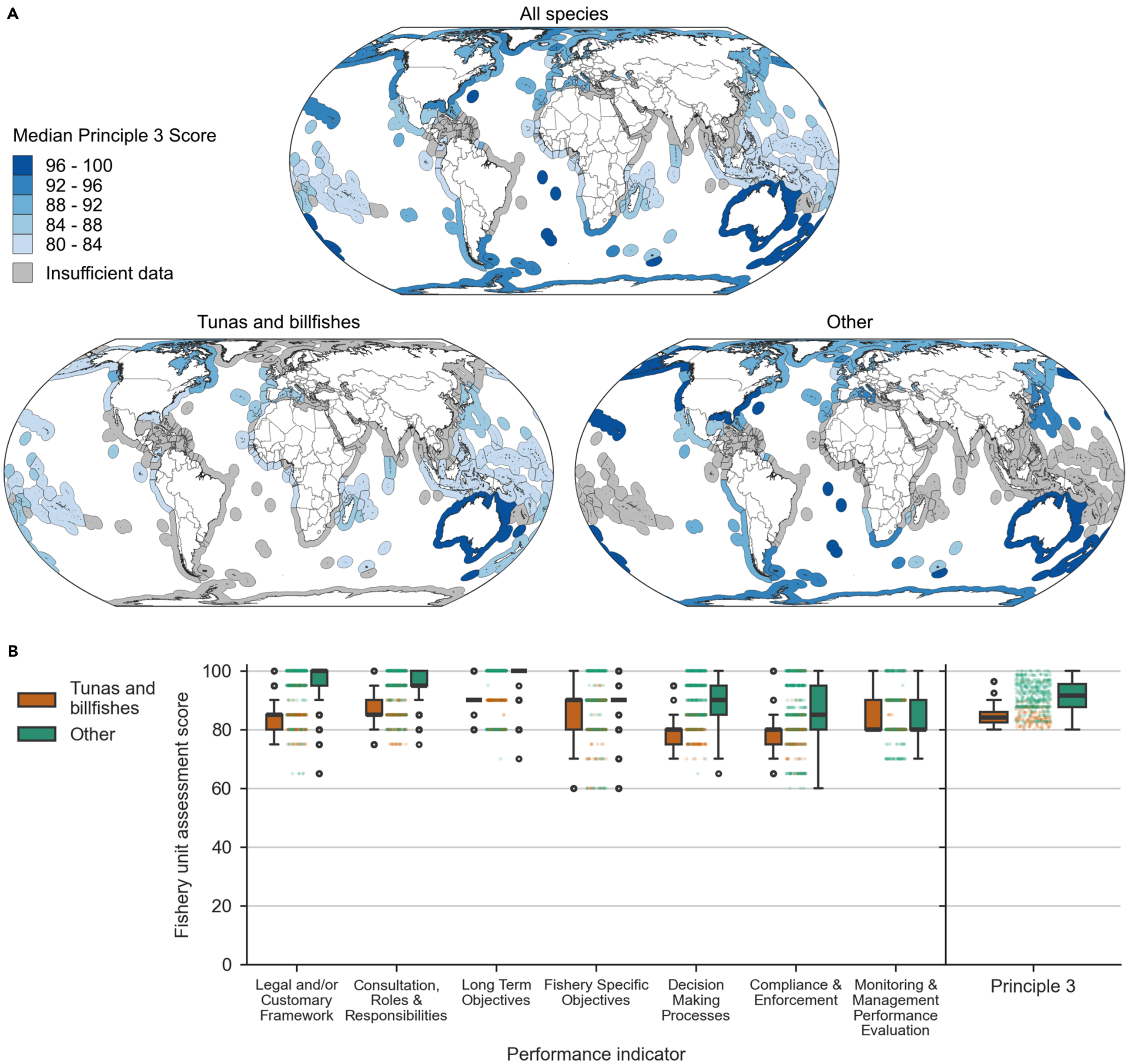

Figure 4. MSC Principle 3 and underlying performance indicator scores across fishery units

(A) Median MSC Principle 3 assessment score, assessing management effectiveness. The higher the MSC Principle 3 score, the lower the management vulnerability indicator of the fishery unit. Scores are aggregated by the EEZ(s) in which the fishery operated. A single fishery unit may operate across multiple EEZs, in which case the score was applied to each EEZ in which the fishery unit operated. Only fishery units that passed the assessment and therefore scored at least 80 were included.

(B) MSC fishery assessment scores for the seven performance indicators of Principle 3 and overall Principle 3 score, which evaluate management effectiveness. Scores are separated by fishery units that target tunas and billfishes versus those targeting other species. Boxes show IQR with bold lines showing median. Whiskers show lowest datum within Q1 − IQR × 1.5 and highest datum within Q3 + IQR × 1.5, while black open points show observations outside these fences. Colored points show individual fishery unit scores.

performance indicator and the compliance and enforcement performance indicator (Figure 4B). The distribution of monitoring and management performance evaluation scores showed the least difference between tunas and billfishes and other species, indicating that challenges in reaching higher performance here were not specific to tuna fisheries.

The lowest scores for fishery units targeting tunas and billfishes were generally in the decision-making processes and the compliance and enforcement performance indicators; in the latter, scores were limited by criteria evaluating sanctions and monitoring, control, and surveillance implementation. All included fisheries met at least the minimum requirements of having sanctions to deal with non-compliance, and there is no evidence of systematic non-compliance, but about 20% of tuna and billfish fishery units included did not meet criteria to show that sanctions are consistently applied. Additionally, 90% of tuna and billfish fishery units did not meet criteria to show that sanctions demonstrably provided effective deterrence. Although all included fisheries have implemented at least ad hoc or isolated monitoring, control, and surveillance mechanisms, and there is a reasonable expectation of their effectiveness, 88% of included tuna and billfish fishery units did not meet criteria to show that these mechanisms represent a comprehensive and cohesive system that demonstrates consistent ability to enforce management measures. In criteria evaluating decision-making processes, tuna and billfish fishery units demonstrated that decision-making processes responded to serious or important issues identified in relevant research, monitoring, evaluation, and consultation in a timely manner but not to all issues identified, thereby limiting assigned scores.

When evaluated based on the EEZ(s) in which fishery units operate, fishery units targeting tunas and billfishes tended to score less favorably in MSC Principle 3, compared with those targeting other species in the same EEZ (Figures 4A and S4). Fishery units operating in EEZs of St Helena, Ascension and Tristan da Cunha, and Heard and McDonald Islands had the highest (most favorable) median Principle 3 score (98.8) across all species and consistently higher scores in all performance indicators (Figure S4), but all had five or fewer fishery units. Fishery units operating in the Australian EEZ, including Macquarie Island and Norfolk Island EEZ, scored the next highest (median 97.5) across 32 fishery units (Figure 4A). This contributed to overall lower management vulnerability indicator values, and thus lower median risk, observed for fishery units operating in the Australian EEZ (Figures 2B and S2).

Highest aggregated risks across fishery units targeting non-tuna or billfish species were observed in the Northeast Atlantic Ocean and in part of the Chilean EEZ, (Figure 2B; median risk $\geq$0.27, except in coastal Iceland where median risk is 0.22). Only one fishery unit targeting these other species operated in the higher-risk area of the Chilean EEZ, which was a pelagic stock with very high exposure to EEZ shift and high seas shift. Most of the fishery units targeting these other species that operated in the higher-risk area of the Northeast Atlantic where median risk $\geq$0.27 (n = 175) targeted species in the cod, hake, and haddock group while others targeted those in the herring, sardines, and anchovy group and flounder and halibut group, all of which had intermediate risk (Figure 1). Because these fishery units target stocks that generally overlap many EEZs, exposure of EEZ shift and vulnerability from governance complexity were generally high (87% had EEZ shift exposure $\geq$0.60%, and 68% had governance complexity vulnerability $\geq$0.76). In contrast, management vulnerability for these fishery units (median 0.12) was only slightly higher than the median across all fishery units targeting non-tuna or billfish species. This management vulnerability was in part attributed to the MSC Principle 3 performance indicator regarding the monitoring and management performance evaluation, which consistently scored least favorably among the seven performance indicators for these fishery units. About 60% of these fishery units were unable to meet criteria for mechanisms to evaluate all parts of the fishery-specific management system (rather than just key parts) or criteria for the fishery-specific management system to undergo regular external review. Similar to the challenges for fishery units targeting tunas and billfishes, over 55% of these higher-risk fishery units in the Northeast Atlantic did not have a cohesive and comprehensive monitoring, control, and surveillance systems with a demonstrated ability to provide enforcement, although all did have monitoring, control and surveillance mechanisms with a reasonable expectation of their effectiveness. Regarding the fishery-specific management system, over 35% of these fisheries could not meet criteria for decision-making processes that respond to all issues identified or criteria for formal reporting on fishery performance and management actions to all interested stakeholders, although all these fisheries do have decision-making processes that at least respond to serious issues and make at least some information available to stakeholders. Finally, all these fisheries had objectives implicit within the management system that were consistent with achieving a sustainable fishery, but over 20% of these fisheries did not have short- and long-term objectives that were well defined and measurable.

Risk estimate sensitivity

Sensitivity analyses showed variation in risk to be influenced most by inclusion/exclusion of individual indicators, with relatively small influence from either aggregation method or indicator weighting (Figure S5). The inclusion/exclusion sensitivity analysis showed that the management vulnerability indicator accounted for the greatest variability in risk (Figures S6 and S7), as expected, given that this indicator had the highest overall weight (7/8 of overall vulnerability), and our sample only included fisheries with low management vulnerability, given that they had already met MSC requirements. Uncertainty, measured by the standard deviation across Monte Carlo simulations, was generally highest and most varied for exploitable biomass decline (Figure S8). Finally, when grouped by species group, the variation in exposure to exploitable fish biomass decline and high seas shift under mitigation scenario SSP1-2.6 was small, compared with the high-emissions scenario SSP5-8.5 presented here, but the latter generally showed slightly higher median exposure (Figure S9).

DISCUSSION

By combining exposure to stock shift and biomass decline with vulnerabilities of fishery management systems, we identified the risk of fishery units in the MSC program to potential management disruptions by 2050 under a high greenhouse gas emissions scenario. As formulated, relatively high levels of risk are observed when exposure and vulnerability are both relatively high. Fisheries targeting tuna and billfish species were at relatively higher risk (Figure 1), followed by those targeting small pelagic and demersal fish species, particularly in the Northeast Atlantic Ocean and Barents Sea (Figure 2B). To reduce their risk, fisheries should advocate for strengthening the processes around effective decision-making among the many countries involved in managing transboundary stocks, particularly tunas and billfishes. We now turn to consider these two components of risk—exposure to climate impacts and vulnerabilities in fisheries management.

Exposure to climate change effects will challenge fisheries across the globe

While several fishery units had stock shift values of 0, the indicator for exploitable biomass decline rarely approached 0 (the lowest quartile was 0.14 compared with 0 for high seas shift and EEZ shift). This was expected as it has previously been reported that by mid-century, under a high-emissions scenario, most of the global ocean area will face exploitable fish biomass declines of 10% on average.[37] Biomass losses by 2050 under SSP5-8.5 are generally expected to be greater around tropical latitudes such as Oceania.[37–40] Our findings for tunas, distributed mainly in tropical waters, are consistent with these predictions. All fishery units evaluated had low to moderate exploitable fish biomass decline exposure ($\leq$0.43), due in large part to the most extreme predicted declines only happening toward the end of the century and also lack of representation of fisheries in areas of extreme predicted decline such as the Azores and Kuwait.[37]

The lower exploitable biomass decline observed for fishery units targeting stocks toward higher latitudes in the Barents Sea, northern Baltic Sea, and Antarctic aligned with predictions of only small decreases, insignificant changes, or increases in these areas by 2050 under the high-emissions scenario.[37,41,42] Low exploitable biomass decline for fishery units targeting stocks in the Gulf of Maine and Nova Scotian shelf by 2050 under a high-emissions scenario is consistent with projections from a related study,[37] but variability among model predictions is high for this region[37] (Figure S10), and regional models suggest a reorganizing of food webs with negative impacts to commercially important species.[43,44] Studies projecting low biomass decline in the Gulf of Maine and Scotian shelf by 2050 also project larger biomass declines by 2091–2100 under the same high-emissions scenario,[37,38] suggesting higher exposure in the longer term.

The large indicator values for EEZ and high seas shifts for tuna and billfish fisheries (Figure 2A) were expected given the large-scale migration patterns in these species. Climate change is predicted to substantially shift the range of these migrations as ocean conditions change.[45–47] This includes tuna stocks shifting away from EEZs of Pacific Small Island Developing States (who financially benefit from tuna-fishing access fees) toward the high seas.[45] The high indicator values for EEZ shift and high seas shift of fishery units targeting other pelagic and demersal fish groups in the Northeast Atlantic Ocean and Barents Sea align with studies already observing changes in the distributions of species in these areas[18,48] and predicting further shifts as ocean temperatures continue to change.[49–51]

In contrast, invertebrate species groups tended to have lower indicator value for EEZ and high seas shifts, compared with fish groups (Figure 2). Combined with lower governance complexity, invertebrate species had lower overall risk, compared with fish groups. Most invertebrates in the MSC program are either benthic, such as bivalves, or are with localized population structures, such as crabs and shrimps. These species may suffer localized climate-driven impacts not captured by our exposure indicators, such as acidification and heatwaves, which means our results are potentially underestimating the need for more responsive tactical measures or novel solutions such as translocation.[52,53] The lower risk of stock shifts across jurisdictional boundaries reduces the complexity of addressing these effects, as they will less frequently require difficult negotiations or suffer from multi-country decision-making delays. Most notable exceptions are represented by a few MSC-certified pelagic invertebrates including squids and krill. Our EEZ shift and governance complexity indicators were low for fishery units targeting Antarctic krill (*Euphausia superba*) (0 and 0.13, respectively), which does not cross multiple EEZs but is managed by multiple countries under the Antarctic Treaty[52] through the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR). As potential modifications to krill harvest targets are being discussed in response to climate-driven ecosystem changes,[53,54] risks of delayed action due to multi-country, consensus-based governance therefore still apply. Yet, overall, these results suggest that at least for benthic and demersal invertebrate populations with localized distributions, managing climate change effects might represent a less daunting challenge than for pelagic, highly migratory fisheries.

Addressing potential vulnerabilities in multinational management systems could mitigate risk

Fishery units targeting tunas and billfishes had the highest governance complexity values because many countries are typically involved in managing stocks. The RFMOs under which tuna stocks are managed comprise more member nations than would normally manage shared stocks across neighbouring EEZs, as they can include, as per the 1995 United Nations Fish Stocks Agreement, coastal states and distant water fleets with an interest in the fish stock.[55] Five RFMOs are responsible for management of tuna and tuna-like species, covering the majority of global high seas areas, all with 15 or more members (including the European Union as a single member).

Studies have examined the effectiveness of RFMOs in managing fishery resources to mitigate overfishing and control unregulated non-members, or free-riders, from fishing a stock. Multiple studies have concluded that the higher the number of parties competing for the resource, the lower the chance of a stable organization with full cooperation, in part due to higher chances of conflicting interests and a greater incentive to free-ride.[15,16,56,57] However, if full cooperation and agreement is reached, then the payoff will be much greater relative to conditions without full cooperation. A 2021 study in which 40 stakeholders in the Western and Central Pacific Fisheries Commission (WCPFC) were interviewed showed clear consensus in the perception that the large number and heterogeneous interests of WCPFC members inhibited the ability to come to agreements on key issues.[58] Further complicating tuna management, the substantial exposure to high seas shift makes it likely that tuna stocks will shift between RFMOs,[45–47] particularly between WCPFC and the Inter-American Tropical Tuna Commission (IATTC), highlighting the additional need for comprehensive frameworks for cooperation between these RFMOs.[6,21,59]

Challenges of managing highly migratory stocks are also evident in management vulnerability values, where tuna and billfish fishery units generally had higher values than other fishery units. Among the performance indicators considered under MSC Principle 3 (i.e., the management vulnerability indicator), the lowest scores for fishery units of tunas and billfishes were generally in the decision-making processes performance indicator and compliance and enforcement performance indicator (Figure 4), which reflect the challenge of involving a large number of parties in making decisions, as well as the difficulties of monitoring fisheries on the high seas. Specifically, tuna fisheries had relatively lower scores in implementing sanctions consistently with evidence of efficacy, responding to issues in a timely manner and implementing comprehensive, cohesive, and consistent monitoring, control, and surveillance systems. While these scores meet MSC requirements, other studies have highlighted these as areas that need strengthening, often noting the lack of cooperation among members, differing interests, and resistance to change as obstacles.[13,60–62] In response, decision-making processes within RFMOs need to evolve to be more flexible and timely, with more efficient processes for participation, to better adjust to changing fishing areas and catch availability.[21,22,62]

Fisheries targeting tunas and billfishes are an important component of the global seafood industry,[63] with many communities benefiting, especially in the Western Central Pacific Ocean.[45,64] RFMOs often manage several important tuna stocks fished by many fishing nations, which also represent key resources for a wide-reaching trade network of buyers, processors, and retailers that might span multiple continents.[61,65,66] Therefore, climate change impacts on tunas in a given region are likely to affect many harvest and post-harvest jobs and consumers in multiple countries simultaneously. Accordingly, tuna RFMOs are actively adopting new resolutions and plans of action to incorporate climate science information into their advice and decision-making (e.g., WCPFC[67] and ICCAT[68]). For example, WCPFC is considering potential changes to catch allocations in light of projected stock shifts to account for rights for Pacific small island nations predicted to lose access in the future.[6]

When aggregated to areas of fishery operation, the highest median risk across fishery units targeting non-tuna or billfish species was observed in the Northeast Atlantic Ocean. For these fishery units, high vulnerability resulting from governance complexity, combined with high EEZ shift exposure, highlights a potential susceptibility to management disagreements.[57] These factors contributed to disagreements in management of the Northeast Atlantic pelagic fisheries that occurred between multiple countries with differing interests.[19,20,57] The disagreements resulted in decreased management performance and subsequent suspension from the MSC program of fisheries targeting Northeast Atlantic pelagic stocks, such as Northeast Atlantic mackerel, for failing to have an agreed harvest control rule across all fishing countries involved.[19,65,69] Lower scores in the Principle 3 performance indicator regarding legal frameworks for the Northeast Atlantic pelagic fisheries, due to issues with international cooperation and dispute resolution mechanisms, highlighted areas that, if strengthened earlier, may have reduced impacts of conflicts.[19,65,69] Fisheries in the region should prepare for potential future risks by ensuring the implementation of well-defined and measurable short- and long-term objectives in the fishery management plan, which will increase the capacity to monitor progress and sustainability of target stocks. Additionally, ensuring that the external review of the fishery management system is comprehensive and regular, including evaluating its robustness to predictable and unpredictable exogenous shocks, is likely to help with identifying new issues with sufficient foresight. To prevent issues from escalating and to increase stakeholder support of decisions, improvements could also be made for processes to respond even to issues deemed less important and for increasing formal reporting on performance and actions. Processes for regular external review of the management system facilitate the incorporation of diverse perspectives and knowledge sources, while also ensuring accountability of decision-makers and decisions—both important attributes for climate resilient fisheries management.[9] Without this, fisheries risk missing opportunities or information that could help identify or mitigate future impacts and ensure continued robustness. A long history of scientific cooperation in the Atlantic region, thanks to the activities conducted by the International Council for the Exploration of the Sea (ICES), may be an enabling factor facilitating reviews without excessive burden for each individual management system.

Recommendations for future risk evaluations

MSC-certified fisheries include a diverse set of species, gear types, and scales, but coverage can be regionally biased, for instance, the lack of representation of non-tuna species in equatorial regions.[37,50,66] Future analyses comparing risk across a more representative sample of global fisheries could improve our understanding of regional and taxonomic patterns. Including fisheries that are not certified to the MSC standard but for which MSC governance scores exist, such as fisheries that have undergone a pre-assessment,[66] could broaden the sample of fisheries beyond those that are MSC-certified.

This analysis focused on climate change exposures predicted to occur by mid-century (2050) under a high-emissions scenario, in line with a precautionary approach evaluating a pessimistic scenario. Ideally, it is preferrable to compare multiple scenarios. Existing data limitations restricted the ability to project risk under alternate scenarios, but it was possible to evaluate exposure indicator values for high seas shift and exploitable fish biomass decline under the alternate strong mitigation scenario (SSP1-2.6). As expected, based on related research,[37,70] the high-emissions scenario generally showed only slightly higher exposure (Figure S9). This is likely because total uncertainty before 2050 is generally dominated by model structure uncertainty, with scenario uncertainty becoming dominant from about mid-century and later.[71] It could be reasonably hypothesized that under alternate futures with more mitigation (for example, SSP1-2.6), risks to fisheries would be lower than those presented here.[37,72]

The larger uncertainty in the management vulnerability indicator (Figure S8) reflects the variation of assessment scores across the seven performance indicators for a given fishery unit. This illustrates that most fishery units do not score evenly across the performance indicators for management effectiveness but rather have strengths and weaknesses. However, the MSC fisheries standard was not developed to specifically evaluate climate change vulnerability, so a deeper analysis of which aspects of management captured in Principle 3 are the most precise proxies of governance resilience in this regard[6,9] may allow this indicator to provide a more targeted evaluation of where improvements are needed most to mitigate risks.

Exposure to exploitable biomass decline showed the largest standard uncertainties across fishery units, likely due in part to the stock area polygons within which biomass decline rates were sampled. Many stock areas were delineated by statistical or management areas, for example, ICES polygons, which often overestimate the species' actual distribution and habitat preferences. Future studies could potentially decrease this uncertainty by using more precise species distribution estimates. However, the simplicity of our approach allowed for consistent application across diverse stocks.

We estimated uncertainty for each measure using available uncertainties in input datasets, but we did not evaluate the sensitivity of results to the structure of the models that produced the input data, for example, models in the fisheries and marine ecosystem model intercomparison project (FishMIP) ensemble used for biomass estimates or the dynamic bioclimatic envelope model (DBEM) model used for stock shift predictions. Uncertainties and sensitivities of these models are discussed in other studies.[37,38,50,73–83] Some key methodological uncertainties associated with high seas and EEZ shift input data include uncertainties in species' distribution maps used as input, and uncertainties in the complex biogeochemical and ecological interactions of selected Earth system models (ESMs).[50,74,75] Key uncertainties in the FishMIP ensemble projections include those stemming from differences in how ecosystem models handle interactions and movements of organisms, model the effect of physical factors like temperature on organisms, and integrate ESM forcing variables.[37,38,73] Further, FishMIP and DBEM model outputs assumed absence of fishing.[37] Research suggests that FishMIP ensemble exploitable biomass decline and DBEM stock shift prediction outputs are robust for global analysis,[50,74,75] but here, we downscaled results to assign risk to individual fishery units, thereby likely underestimating actual variability among fishery units.

We evaluated fisheries on a global scale, and such results here are not intended to provide accurate predictions of absolute risk to individual fishery units but rather to compare broad risk patterns across regions and species groups of certified fishery units to identify the types of fisheries relatively more at risk. This required making simplifying assumptions to assess exposure and vulnerability across diverse fisheries and regions. Risk assessment of individual fisheries would likely be more nuanced and built upon detailed information about the threats and governance properties of those systems. Future work could also evaluate the possibility of interactions between indicators of exposure and vulnerability.

Conclusions

This study provides a first overview of the future risks to sustainable management of wild capture fisheries by combining existing projections of climate change impacts with a novel governance proxy based on ecolabel management data. Focusing on MSC-certified fisheries, which already meet robust management standards, we found that risks from stock shifts and biomass decline were low to moderate. The highest risk recorded for these fisheries was less than 50% of our index scale, and it can be expected that MSC-certified fisheries are faring better than many other fisheries lacking data and resources to monitor and regulate their activities.[84] This evaluation allowed for comparisons across diverse fisheries, including 135 target species operating across the globe, providing detailed insights into how their management systems will need to prepare, like all natural resource extraction activities, to adjust to future challenges. We found that tuna and billfish fisheries will face higher risks to sustainable management from stock shifts and biomass decline relative to the other fisheries, primarily due to their highly migratory nature, followed by small pelagic fisheries. Most RFMOs managing tunas and billfishes are working to integrate climate considerations in management, including resolutions to incorporate climate considerations in their scientific advice.[6] Areas that will need increased focus in the future are likely to include the ability to review management systems in a timely fashion, the importance of setting long-term management goals, and the ability to appropriately monitor and enforce regulations. Exposure to stock shift and biomass decline are far from unique to these fisheries, and these priorities apply to fisheries worldwide. Our study underscores the urgent need for cooperative, climate-adaptive management to address stock shifts and biomass declines and to ensure sustainable seafood supplies and livelihoods globally.

METHODS

Below, we describe the datasets used on stocks, fisheries, climate change, and social-ecological indicators and summarize the different components of the methodology. We provide a more detailed explanation in the supplemental experimental procedures.

We summarize published information from complex climate projection models in a spatially explicit climate change risk evaluation following IPCC frameworks.[30,72] In this study, risk is defined comparably to the IPCC[30,85] report[30] as the potential of fisheries to be adversely affected by climate change arising from the interaction of hazards, exposure, and vulnerability. Hazard is defined as an event or trend that could cause social or ecological damage or disruption.[30,35] Here, we considered the combined hazards of productivity declines[86] and movement of stocks out of historical fishing grounds,[87] as well as the risk of these hazards impairing the management performance of fisheries across the globe. We combined multiple indices measuring various aspects of each fishery's climate exposure and management vulnerability into an overall risk value for the fishery.

Fishery units and fish stocks

We defined fisheries by the individually assessed fishery units in the MSC program. The individual fishery unit that is assessed, and may carry the MSC status, is the combination of the target stock, fishing method, and vessels or operators pursuing the stock.[88] A certain stock may have multiple fishery units targeting it, but a fishery unit does not target multiple stocks (see supplemental experimental procedures for exceptions). Our analysis focuses on 661 fishery units in the MSC program as of

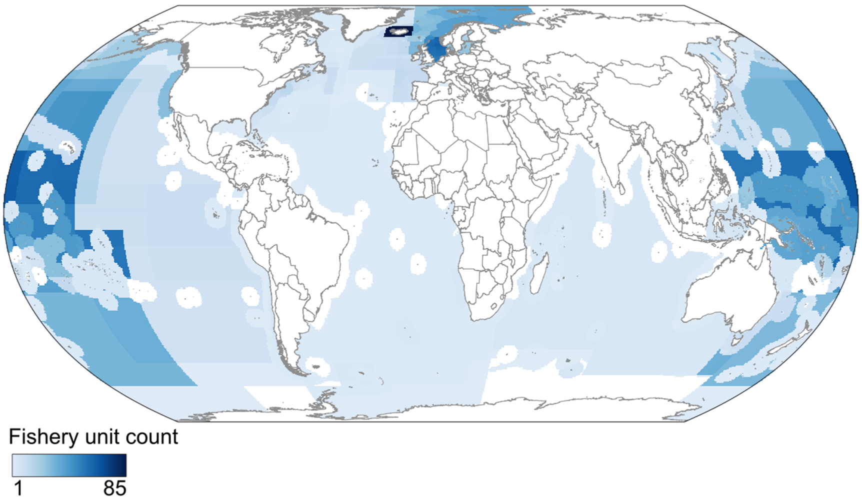

Figure 5. Areas of operation of fishery units in the MSC program included in the study

Areas estimated for each of 661 fishery units from descriptions of geographic area in MSC assessment reports.

31 December 2022, which had been certified against the MSC fisheries standard v2.0 Default Normative Tree.[28] In order to compare assessment scores across fisheries and control for variations across different MSC fisheries standard versions, only those that were assessed against the same assessment version were included. The highest density of 85 overlapping fishery units was around Iceland, but high density was also observed in Northern Europe and Western Central Pacific waters (Figure 5).

The geography of each fishery unit was delineated in two ways—by the geographic area of the target stock and by the geographic area where the fishery unit operated (which may or may not overlap the entire stock distribution). The spatially explicit, stock-based indicators of EEZ shift, high seas shift, fishable biomass decline, and governance complexity were calculated based on the geographic area of the targeted stock. The aggregation of risk values from fishery units to grid cell or EEZ (s) was based on the geographic area where the fishery unit operated. In total, 263 stocks of 135 species were identified as being targeted by the 661 fishery units, including 33 different gear types or fishing methods.

The public certification report from the MSC fishery assessment of the fishery unit was the main source of information for both fishery unit area and identification of the target stock and target stock area. The public certification report is the final report of the fishery assessment, which details all relevant background and scores related to each fishery unit's assessment. All reports are available online.[32]

Risk assessment framework

Determining fisheries hazards

We considered two main climate-driven hazards for the context of exposure and vulnerability components of risk: stock distribution shifts and decline in productivity. These have been observed to cause conflict and disruption to fishery management and stock health in many parts of the world.[1,40,59] We evaluate exposure to these hazards (see below) using published datasets[37,50] that modeled projected impacts under a high climate change emissions scenario, RCP8.5 or SSP5-8.8, representing continued fossil fuel development.[72] The high-emissions scenario used here is useful in considering a precautionary approach to assess risk under a plausible worst case scenario.[85,89,90] We acknowledge that this is an extreme climate change scenario[91]; however, we were not able to compute the risk evaluation under alternative emissions scenarios due to limitations of the published datasets. Where data were available, we compared indicator values under alternate scenarios. Data were available under both the high-emissions scenario SSP5-8.5 and the strong mitigation scenario SSP1-2.6 for two indicators of exposure (high seas shift exposure and exploitable fish biomass decline; see below), so these indicators were evaluated under each scenario and compared to evaluate the influence of the scenario. Because this sensitivity testing and related research demonstrate only small variation between scenarios prior to 2050, with model uncertainty only becoming more dominant later,[37,70,71] the single high-emissions scenario used here is still relevant to the mid-century time period evaluated here.

Determining fisheries' exposure and vulnerability to hazards

Both the exposure and vulnerability components of risk were derived from multiple indicators, chosen to measure important aspects of the fishery's exposure and vulnerability, relevant to the hazards of stock shift and productivity decline, based on literature. Proxy measures of indicators (Figure 6; Table S1) were selected to prioritize datasets that covered the global scope of fisheries of interest with minimal additional resources required to curate the data.

For exposure, we developed three spatially explicit indicators measuring the extent of stock shift between neighboring EEZs of the target stock, the extent of stock shift between national jurisdiction and the high seas of the target stock, and the extent of exploitable biomass decline in the targeted stock area. For vulnerability, we developed two indicators. One used MSC management effectiveness (Principle 3) scores as a proxy measure of management vulnerability to evaluate management systems with some of the attributes needed to adapt to and cope with stock shift and productivity impacts. The second used the number of EEZs overlapping the target stock as a proxy measure of the number of countries involved in decision-making and thus governance complexity (Figure 6).

All indicators were developed to reflect a scale from minimum to maximum exposure or vulnerability likely to contribute to impairment of management performance and thus stock productivity. Each indicator was rescaled to values between 0 and 1 before computing risk so as not to unevenly weight indicators

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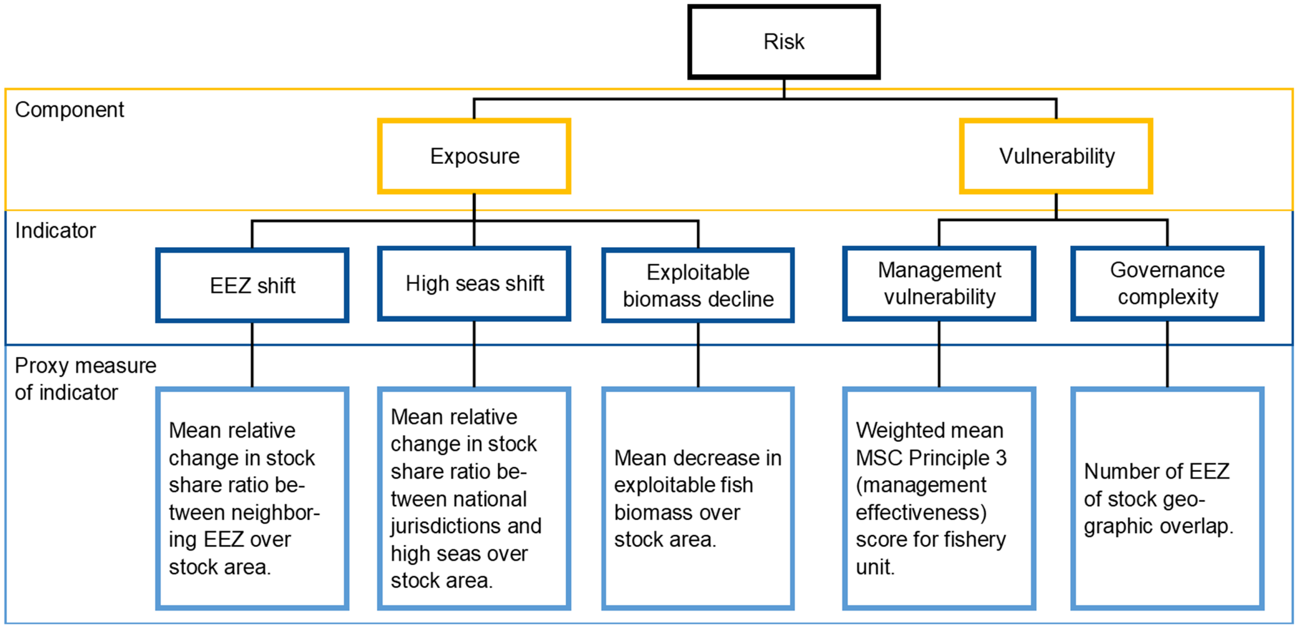

Figure 6. Risk assessment framework used, showing indicators that made up exposure and vulnerability components used to evaluate risk
Proxy measures detail the specific measure used to approximate the indicator.

on different scales.[92,93] We consider fishery units with indicator and risk values from 0 to 0.2 as very low, 0.2 to 0.4 as low, 0.4 to 0.6 as moderate, 0.6 to 0.8 as high, and 0.8 to 1 as very high.

The EEZ shift indicator and high seas shift indicator were computed from published projections on the effects of climate change on shared stock catch ratios across jurisdictions.[50] As these projections were existing outputs of two previous studies (Palacios-Abrantes et al.[50] and Palacios-Abrantes et al.,[70] rather than modeled specifically for the objectives here, the methods that produced the EEZ shift projections differed slightly from the methods that produced the high seas shift projections. For projections of shifts between EEZs, transboundary species were identified then stock share ratios were computed for each EEZ-neighbor pair (for example, between the United States and Canada Pacific EEZ-neighbor pair) for every species identified as transboundary.[50] For projections of shifts between high seas, straddling species were identified then stock share ratios were computed for each high seas area (delineated by tuna RFMO area for stocks identified as highly migratory or ocean basin for other stocks) and neighboring area of national jurisdiction (delineated by shelf areas classified by biogeographic realm[94]) for each species identified as straddling.[70]

Changes in stock share ratio across neighboring areas for both EEZ and high seas projections were projected using the DBEM extensively described in Cheung et al.[39,75,95] Briefly, the DBEM estimates the distribution of marine fish and invertebrates globally on a 0.5° × 0.5° grid. Initial species distributions are based on the Sea Around Us (www.searoundus.org) algorithm, including depth and latitudinal range, and known FAO statistical areas and expert range maps. For each species, the model projects its distribution as a response to ocean conditions (e.g., temperature, salinity, pH) and habitat suitability. Since Palacios-Abrantes et al.[50] and Palacios-Abrantes et al.[70] were conducted at different times, oceanic conditions were projected using slightly different conditions, depending on available information at the time. Oceanic conditions for EEZ shift projections were calculated following the coupled model intercomparison project (CMIP) 5 protocol, using the Geophysical Fluid Dynamics Laboratory (GFDL) Earth system model (ESM) following RCP8.5.[50] Oceanic conditions for high seas shift projections were calculated following CMIP6 protocol, using GFDL, Institut Pierre-Simon Laplace (IPSL), and Max Planck Institute (MPI) ESMs following SSP5-8.5.[70] CMIP6 is an improvement on CMIP5, which includes updated oceanographic drivers, higher resolution, and updated emissions scenarios, overall exhibiting higher sensitivity to climate change, but marine biomass trends remain similar between both CMIP5 and CMIP6 under a high-emissions scenario by 2050.[38]

For the target stock of each fishery unit, we calculated Glass's delta (Δ)[96] as in Equation 1. We compared mean projected mid-21st-century stock share ratios between neighboring EEZ and high seas realms for 2041–2060 ($\overline{x}_{mid}$) with the mean modeled historical stock share ratios between the same neighboring EEZs (in 1951–2005 for EEZ shift) and high seas realms (in 1951–2014 for high seas shift) ($\overline{x}_{his}$), relative to the standard deviation of historical stock share ratios (σ_{his}). Differences in historical periods were due to projections having been calculated under the CMIP5 and CMIP6 protocols, respectively. We then averaged Δ across all EEZ-neighbor or high seas realms pairs of the targeted stock to indicate mean EEZ shift or high seas shift effect size, respectively.

$$\Delta = \frac{|\overline{x}_{mid} - \overline{x}_{his}|}{\sigma_{his}} \qquad \text{(Equation. 1)}$$

Related studies interpret Δ = 2 as the threshold for a significant stock shift[50,70] since this is considered a large effect with only 19% of the two distributions overlapping.[96,97] Many values of mean shift Δ here fell beyond 2; so in order to interpret a large mean Δ as a fishery unit with significant exposure to EEZ or high seas shift, while also preserving as much variation between values as possible and avoiding extreme values overly dominating the scale, the highest exposure for EEZ and high seas shift was set as mean Δ = 4. The mean shift Δ values were then rescaled using a min-max scaler to limit values to between 0 and 1. In this way, a fishery unit that targets a stock with mean Δ $\geq$2 would have an EEZ or high seas shift exposure $\geq$0.5. Final EEZ and high seas stock shift exposure indicator values thus ranged from 0, no exposure to stock shift observed, to 1, maximum exposure to stock shift (mean EEZ or high seas Δ = 4; Figure S11).

To quantify decreases in exploitable fish biomass that the fisheries are projected to be exposed to, we used modeled marine biomass data provided by FishMIP, which works to standardize ensemble projections of marine ecosystem models.[38,73] Projection data provided by FishMIP include biomass variation in the global ocean from historical to mid-century time periods, not including fishing impacts.[37] Marine biomass is here limited to size classes of exploitable fish biomass, from 10 g to 100 kg.[37] Biomass in these size classes were obtained from six global marine ecosystem models (APECOSM[76], BOATS[77,78], DBPM,[79] EcoTroph,[80] Macroecological,[81] and ZooMSS[82]), each forced with up to two CMIP6 ESMs (IPSL and GFDL), resulting in 10 combinations of ESMs and ecosystem models. The ESMs differ in structure and assumptions, such as forcing variables used and plankton taxonomic groups included, but were standardized to the FishMIP protocol to force marine ecosystem models and to account for ESM uncertainty. The FishMIP ensemble of models further allow accounting for structural uncertainty in marine ecosystem models.[38,73] We use simulations projected for the scenario SSP5-8.5.[38] We analyzed projections of the percentage change in exploitable fish biomass for each $1^\circ \times 1^\circ$ grid cell globally relative to mean exploitable fish biomass across 1951–2014.[37,38,73]

We calculated the ensemble mean percentage change in exploitable biomass across the 10 ESM-model combinations for each cell.[38,40,42] We then calculated the mean change in exploitable biomass across all cells overlapping the stock area. To indicate exposure to decreases in exploitable fish biomass, any stock with a mean increase in biomass was reassigned a biomass decline of 0, which would evaluate to a biomass decline exposure of 0.

Values were then rescaled, so final biomass decline exposure values thus ranged from 0, no exposure to fishable biomass decline observed, to 1, maximum exposure to fishable biomass decline (50% exploitable biomass decline; Figure S11). This was in line with related studies that interpret exploitable fish biomass decline greater than 50% to be an extreme situation with a high potential for consequences.[37,38] Further details of the three exposure indicators are described in Table S1 and the supplemental experimental procedures information sections.

The management vulnerability indicator (Figure 6) utilized MSC Principle 3 assessment scores of the fishery unit. Many factors can contribute to complexity, adaptability, and effectiveness of decision-making processes, such as the type of agreements in place and history of cooperation.[7,9] We assumed that MSC Principle 3 scores approximate some of the qualitative differences between adaptability and effectiveness attributes, which can indicate vulnerabilities. Principle 3 of the MSC fisheries standard is a weighted average score of seven performance indicators assessing the effectiveness of management systems and the ability of fisheries to comply with relevant laws and to adapt to changing environmental conditions (Figure 3), which could be associated with important attributes for reducing vulnerability to climate change impacts.[9] All management systems relevant to the fishery are considered and assessed, including relevant RFMO(s) and national and local management agencies and organizations, taking into account the scale and intensity of the fishery.[28]

Each of the seven performance indicators within Principle 3 are evaluated against multiple criteria to assess fishery performance at levels from 60 to 100, with 60 representing minimum acceptable performance, 80 representing best practice, and 100 representing state of the art.[33]. The performance indicator scores are then weighted and aggregated according to the MSC fisheries standard[28] to calculate the overall Principle 3 score, which quantifies the overall performance of the management systems.[33] If a fishery unit does not reach at least 60 for all criteria in all performance indicators, and at least 80 for the weighted average principle score, it fails the assessment.[33] If a fishery unit scores between 60 and 80 for any individual performance indicator, it receives a condition of certification detailing an action plan and milestones required to address the issue and raise the score to 80 by the next assessment cycle.[33] If the fishery is unsuccessful by its next assessment cycle, it must withdraw from the MSC program, and it loses its certification.

We calculated the Principle 3 score of each included fishery unit as the weighted average of the seven reported performance indicator scores, as instructed by the MSC standard.[33,98] We used scores from the latest public certification report of each fishery unit published as of 31 December 2022, which are publicly accessible on the MSC Track a Fishery website (fisheries.msc.org). In total, 211 reports were included, published between 20 April 2017 and 13 December 2022.

A min-max scaler was used to rescale scores to values between 0 and 1, where the minimum was a score of 0 and maximum a score of 100. Although a fishery unit does not explicitly receive a score if it does not meet the minimum sustainability requirement of 80 for the principle (they would simply be recorded as failed), the theoretical range of assessment scores is from 0 to 100. Because a higher vulnerability should coincide with a lower Principle 3 score, we subtracted the scaled value from 1 such that a management vulnerability indicator value of 0 is a Principle 3 score of 100 and the maximum management vulnerability value of 1 corresponds to a theoretical Principle 3 score of 0 (Figure S11).

Although MSC assessment considers the cooperation of all parties involved in management, it does not score fisheries by the number of parties involved. Yet, a greater number of parties, for example governments managing the stock, can decrease the chance of successful full cooperation. Thus, the number of countries involved in management of the targeted stock provides an additional, globally applicable indication of vulnerability of the fishery due to increasing complexity of stock management decisions. In the absence of a definitive dataset of nations managing each included stock, a measure of EEZ overlap was used as a proxy that could be applied globally. Stocks overlapping more EEZs were therefore assumed to be more vulnerable to management impacts from stock shift and productivity decline hazards.[7,15,16]

Unique EEZs were counted based on overlap with the Flanders Marine Institute EEZ from Marine Regions[99] as these aligned best with political differentiations. The number of overlaps was positively skewed with extreme outliers observed, generally from highly migratory tuna stocks. It is generally understood that decision-making complexity increases with the number of parties involved, but it is reasonable to assume that once a certain number of parties is reached the relevant vulnerability from governance complexity should saturate. That is, once the complexity is sufficiently high, risk will also be high if sufficient frameworks to guide multinational cooperation are not in place.[12,100] In the absence of studies on the precise relationship between the number of parties involved and vulnerability to climate change impacts, we used the IQR method to isolate and reassign extreme values in order to avoid a small number of extreme values from dominating the indicator scale, instead assigning a reasonable maximum vulnerability value. In this way, any value above the upper limit, third quartile (Q3) plus 1.5 times the IQR, was reassigned the limit value.[101] The count of EEZ was then rescaled using a min-max scaler to limit values between 0 and 1, where 0 was the minimum observed governance complexity (1 EEZ overlapped), and 1 was the maximum governance complexity ($\geq$9 EEZs overlapped) (Figure S11). Further details of the two vulnerability indicators are described in the supplemental experimental procedures and Table S1.

Risk evaluation

Indicators for exposure and vulnerability components were aggregated to their respective component value using an arithmetic mean of indicator values.[4,93,102] Indicators for exposure (EEZ shift, high seas shift, and exploitable biomass decline) were weighted equally. Vulnerability indicators were weighted so that the indicator for governance complexity would have the same weight on average of each of the seven performance indicators within the MSC Principle 3 management effectiveness score (Figure 3), based on the assumption that governance complexity is as influential as each of the performance indicators, which together encompass broader aspects of susceptibility to impact. The management vulnerability subindicator was therefore assigned a weight of 7/8 of the vulnerability component, and the governance complexity indicator was assigned a weight of 1/8.

Risk is a function of climate exposure and vulnerability of the fishery, where a high vulnerability may compensate for a low exposure, and vice versa.[72,103,104] Thus, risk (R) of each fishery unit (i) was calculated as the geometric mean of the exposure (E) and vulnerability (V) components as in Equation 2.

$$R_i = \sqrt{E_i V_i} \qquad \text{(Equation. 2)}$$

A fishery unit with a maximum possible risk of 1 has the highest chance of facing consequences from stock shift and productivity decline, potentially resulting in impairment of management performance and impacts on stock health.

In order to observe regional or spatial patterns of risk, fishery unit risk was also aggregated to the 0.5° × 0.5° grid cell and to the EEZ(s) of the coastal state(s) where the fishery unit was estimated to be operating. This allowed us to evaluate patterns across ocean areas or jurisdictions. Although risk could be different at smaller scales (e.g., local ports), this choice of resolution balanced availability and uncertainties of global datasets with results that could be actionable for decision-makers. The median risk across all fishery units estimated to be operating in an EEZ (including the 12-nm territorial seas) was calculated based on the overlap of fishery unit areas and EEZ areas.[99] A fishery unit may operate across multiple EEZs, in which case its risk would be applied to each EEZ it overlapped.

In addition to comparing risk across all fishery units, we compared the aggregate risk of fishery units grouped by ISSCAAP group of the target species to observe patterns based on the taxonomic and ecological characteristics. Further, we compared fishery units targeting the highly migratory species of the tuna, bonitos, and billfish species group,[36] managed by RFMOs, with those of other species. These highly migratory species have unique management properties and may be more exposed to shifting stock distributions because of differences in bioecological characteristics and broad geographic distributions.

A Monte Carlo simulation method was used to calculate a final risk and standard deviation for each fishery unit. Monte Carlo methods are advantageous for their ability to test estimators, using data generated from known parameters, to characterize overall uncertainty taking into account the uncertainties in the individual underlying indicators.[105,106] The method involved randomly sampling of the variability (uncertainty space) of each indicator of each fishery unit and recalculating the fishery unit's risk from the simulated indicator values.[107] This was repeated using 10,000 simulations to generate a probability distribution from which standard uncertainty and mean (final) risk were calculated for each fishery unit.

It was not possible to account for covariances among indicators during these simulations; while standard deviations of indicators were specific to each fishery unit, the correlation structure between them was unknown. To evaluate the consequence of not accounting for covariances during these within-fishery simulations, we constructed a covariance matrix from the across-fishery estimates of each indicator (i.e., from the simulation means for each of 5 indicator values and 661 fishery units). We then simulated indicator values from this matrix, accounting for covariances among them, and compared the distributions of risk between scenarios accounting or not accounting for covariances (Figure S1). The medians of the distributions were 0.253 and 0.233, respectively, suggesting that not accounting for covariances during Monte Carlo simulations results in underestimating risk by 2.2 percentage points or a ratio of 0.92. This is expected to have little consequence for our overall conclusions based on point estimates, given that the interest is mainly in comparisons of risk and indicator values across species groups or regions rather than in absolute estimates of these values. We do acknowledge, however, that not accounting for covariances results in a different shape of the risk distribution across fishery units (Figure S1) as well as overestimating the precision of risk estimates generally.

The uncertainty for the EEZ shift, high seas shift, exploitable biomass decline, and management vulnerability indicators was estimated from the variance of measurements in the input datasets and tested in the Monte Carlo simulation. For EEZ stock shift and high seas stock shift, the mean and standard deviation of historical and mid-century annual values of stock share between each EEZ pair or high seas realm pair of each stock were used to generate the sampling distribution and propagate the uncertainty from annual variations upward. For exploitable biomass decline, as the FishMIP outputs were already computed to exploitable biomass change per cell, the mean and standard deviation of exploitable biomass change of each cell across each stock area were used to estimate the sampling distribution and propagate the uncertainty from spatial variation upward. The variation across the 10 ESM-model combinations was not included, but variation across cells (spatial variation) was greater than variation across models (supplemental experimental procedures and Figure S10). The Monte Carlo sample for management vulnerability was drawn from a distribution generated from the weighted mean and weighted standard deviation of performance indicator scores for each fishery unit to propagate the uncertainty from variation across criteria scores.

For the governance complexity indicator, overlaps were considered significant if the intersection area was at least 1% of the stock area or at least 10% of the EEZ area to account for limitations in precision of spatial data. These thresholds were tested through Monte Carlo simulations to estimate uncertainty. Distributions were generated to sample varied overlap thresholds of intersection proportion of stock area and intersection proportion of EEZ area. Assumed thresholds defined what was considered a significant overlap of a stock with an EEZ. Normal overlap threshold distributions were generated with the mean as the threshold of 1% for intersection area proportion of stock area (with standard deviation 0.005) and the mean as a threshold of 10% for intersection proportion of EEZ area (with standard deviation 0.05). This created a distribution to sample for each threshold value, where 95% of values were between 0 and double the selected value used as mean.

To evaluate the influence of each indicator, we analyzed the sensitivity of risk estimates to inclusion/exclusion of each indicator, using the Monte Carlo method. Under each of the 10,000 Monte Carlo simulations, risk was calculated while excluding one indicator at a time but leaving all other indicators the same.

A sensitivity analysis was conducted to evaluate the impact of three plausible factors on the estimated variance of the risk output: (1) indicator weighting tested different weights applied to the indicators in calculating exposure and vulnerability components; (2) inclusion/exclusion excluded one indicator at a time, noting that weights would also be reallocated; and (3) aggregation method tested use of a arithmetic mean versus geometric mean for aggregating exposure and vulnerability components to calculate risk. We used the Sobol' analysis in the SALib Python library.[108,109]

The Sobol' method is a global sensitivity analysis that tests the influence of multiple input factors on output variance by varying input factors both individually and simultaneously.[110–113] The analysis provides results in the form of sensitivity indices describing the relative portion of output variance influenced by the input factor. Sensitivity indices are most commonly computed for first-order effects, the influence of varying a single input factor alone, and total effect, the influence of first-order effects and all higher-order effects including interactions between factors. We used the Sobol' analysis to test varying the three different input factors, similar to OECD,[93] and compared resulting sensitivity indices (see also Table S2).

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to the lead contact, Lauren M. Koerner (lauren.koerner@msc.org).

Materials availability

This study did not generate new unique materials.

Data and code availability

- The code used for this study is available from Zenodo: https://doi.org/10.5281/zenodo.17141646.[114]
- Data used for this analysis on Marine Stewardship Council (MSC) fishery units, including approximate geographic area, area of target stock, and Principle 3 assessment scores, are available from the lead contact upon request.
- The data used for this study, which were generated by previous studies, are available from respective sources as follows: transboundary stock shifts for EEZ shift calculations,[12,115] straddling stock shifts for high seas shift calculations,[70,116] and changes in exploitable fish biomass for exploitable biomass decline calculations.[37]

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AUTHOR CONTRIBUTIONS

Conceptualization, L.M.K., M.C.M., R.J.C.C., and C.L.; methodology, L.M.K., J.P.-A., C.N., M.C.M., T.E.E., E.J., and C.L.; validation, L.M.K.; formal analysis, L.M.K. and M.C.M.; investigation, L.M.K., J.P.-A., C.N., J.B., M.C.M., J.D.E., J.G., C.S.H., and R.F.H.; data curation, L.M.K., J.P.-A., C.N., and J.B.; writing – original draft, L.M.K., J.P.-A., C.N., J.B., M.C.M., T.E.E., J.D.E., J.G., C.S.H., R.F.H., R.J.C.C., E.J., B.P., and C.L.; writing – review & editing, L.M.K., J.P.-A., C.N., J.B., M.C.M., T.E.E., J.D.E., J.G., C.S.H., R.F.H., R.J.C.C., E.J., B.P., and C.L.; visualization, L.M.K. and M.C.M.; supervision, R.J.C.C., B.P., and C.L.; project administration, L.M.K. and C.L.; funding acquisition, R.J.C.C., B.P., and C.L.

DECLARATION OF INTERESTS

T.E.E. is a member of the Marine Stewardship Council Technical Advisory Board.

SUPPLEMENTAL INFORMATION

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CRSUS, Volume *3*

Supplemental information

Climate change risks to future sustainable fishing using global seafood ecolabel data

Lauren M. Koerner, Juliano Palacios-Abrantes, Camilla Novaglio, Julia Blanchard, Michael C. Melnychuk, Timothy E. Essington, Jason D. Everett, Jerome Guiet, Cheryl S. Harrison, Ryan F. Heneghan, Rohan J.C. Currey, Ernesto Jardim, Beth Polidoro, and Catherine Longo

Supplemental items

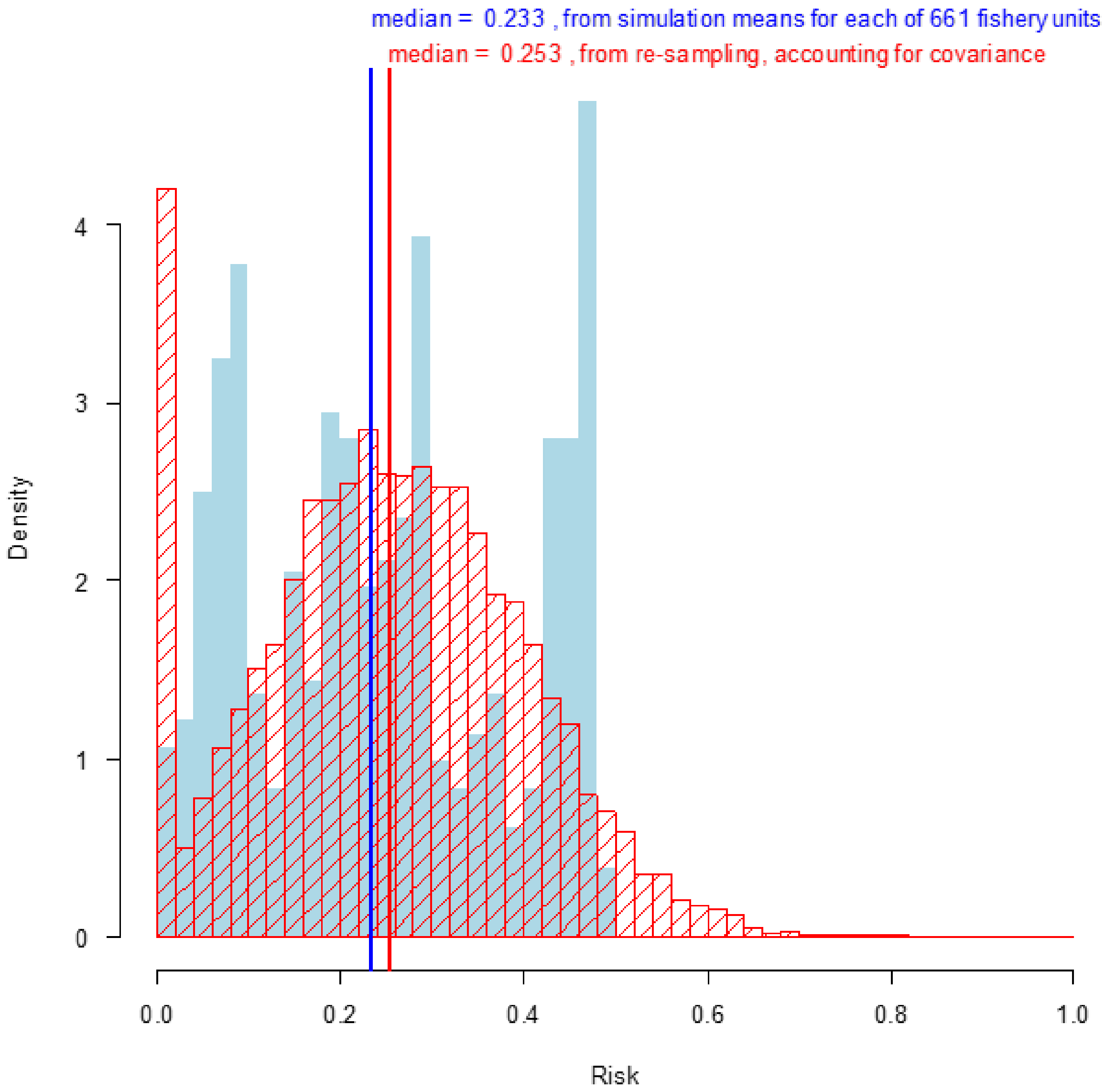
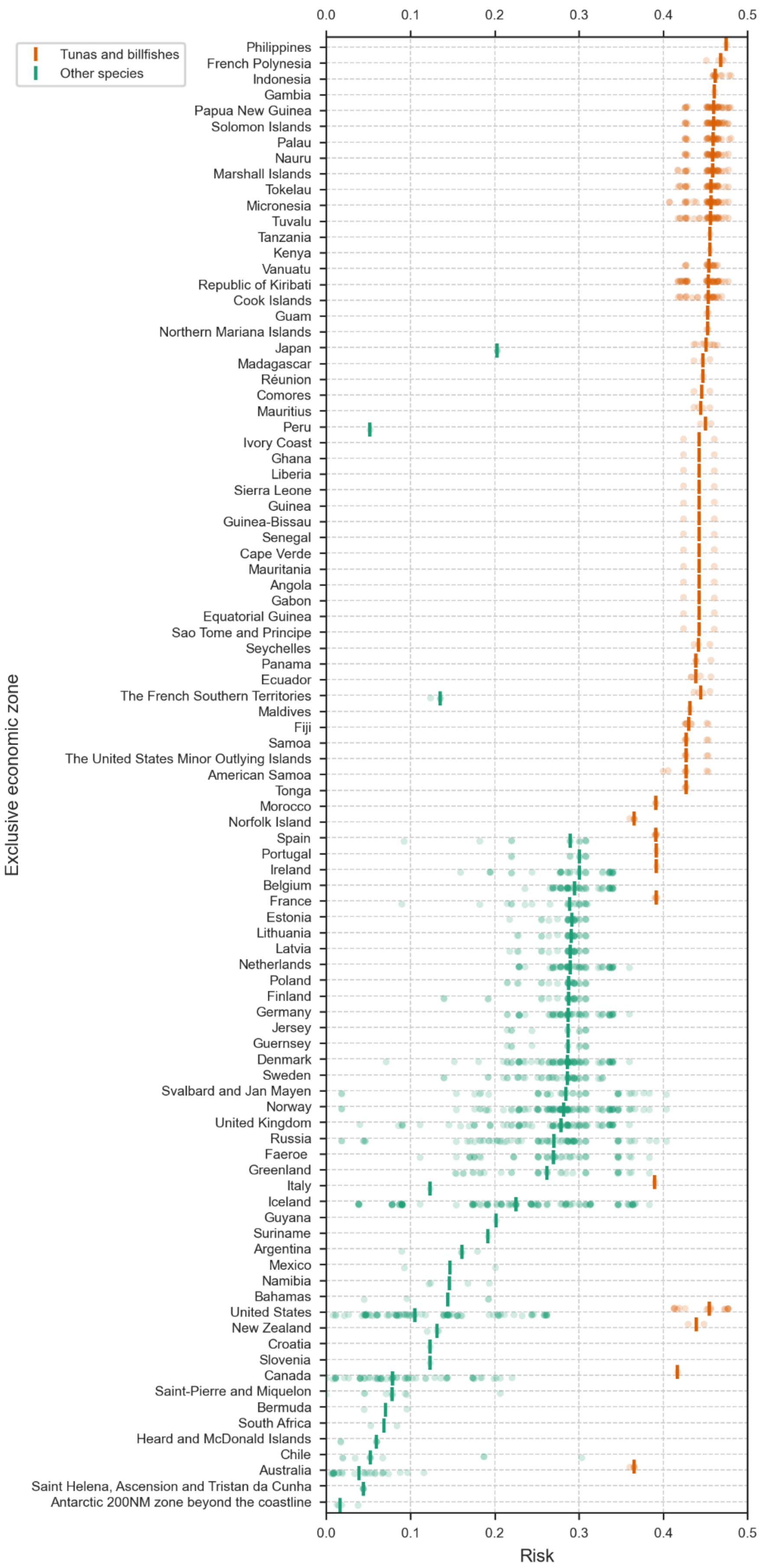


Figure S1. Estimates of risk with and without accounting for covariance among indicators. *Solid blue bars show the histogram of risk calculated from 5 indicator values for each of 661 fishery units. These values are means of the simulated distributions for each fishery unit and indicator. These values were used to generate a 5 x 5 covariance matrix from which 10,000 sets of indicators were sampled, accounting for covariance among indicators. Red hatched bars show the histogram of risk calculated from these re-sampled sets of indicator values. When re-sampling, any negative values of calculated exposure or calculated vulnerability (used in Eq. 1) were assigned a risk value of 0. On the basis of medians of the two distributions, not accounting for covariances among indicators during simulations results in slightly underestimating risk. On the basis of shapes of the two distributions, not accounting for covariances results in some of the highest estimates of risk being underestimated, and in some of the lowest estimates of risk being overestimated.*



Tunas and billfishes
Other species
Exclusive economic zone
Risk
0.0
0.1
0.2
0.3
0.4
0.5
Philippines
French Polynesia
Indonesia
Gambia
Papua New Guinea
Solomon Islands
Palau
Nauru
Marshall Islands
Tokelau
Micronesia
Tuvalu
Tanzania
Kenya
Vanuatu
Republic of Kiribati
Cook Islands
Guam
Northern Mariana Islands
Japan
Madagascar
Réunion
Comores
Mauritius
Peru
Ivory Coast
Ghana
Liberia
Sierra Leone
Guinea
Guinea-Bissau
Senegal
Cape Verde
Mauritania
Angola
Gabon
Equatorial Guinea
Sao Tome and Principe
Seychelles
Panama
Ecuador
The French Southern Territories
Maldives
Fiji
Samoa
The United States Minor Outlying Islands
American Samoa
Tonga
Morocco
Norfolk Island
Spain
Portugal
Ireland
Belgium
France
Estonia
Lithuania
Latvia
Netherlands
Poland
Finland
Germany
Jersey
Guernsey
Denmark
Sweden
Svalbard and Jan Mayen
Norway
United Kingdom
Russia
Faeroe
Greenland
Italy
Iceland
Guyana
Suriname
Argentina
Mexico
Namibia
Bahamas
United States
New Zealand
Croatia
Slovenia
Canada
Saint-Pierre and Miquelon
Bermuda
South Africa
Heard and McDonald Islands
Chile
Australia
Saint Helena, Ascension and Tristan da Cunha
Antarctic 200NM zone beyond the coastline

Figure S2. Median risk across fishery units estimated to be operating in each EEZ. *Exclusive economic zones (EEZs) exclude joint regimes and overlapping claims, and data is separated by fishery units targeting tuna and billfish species (orange) versus those targeting other species (green). EEZs are ordered by highest risk across all fishery units (top) to lowest risk across all fishery units (bottom). Individual fishery units may be assigned to more than on EEZ. Points show individual fishery unit risk values, also separated by target species groups. Possible risk values range from 0 to 1, but the highest observed risk for any fishery unit was 0.48.*

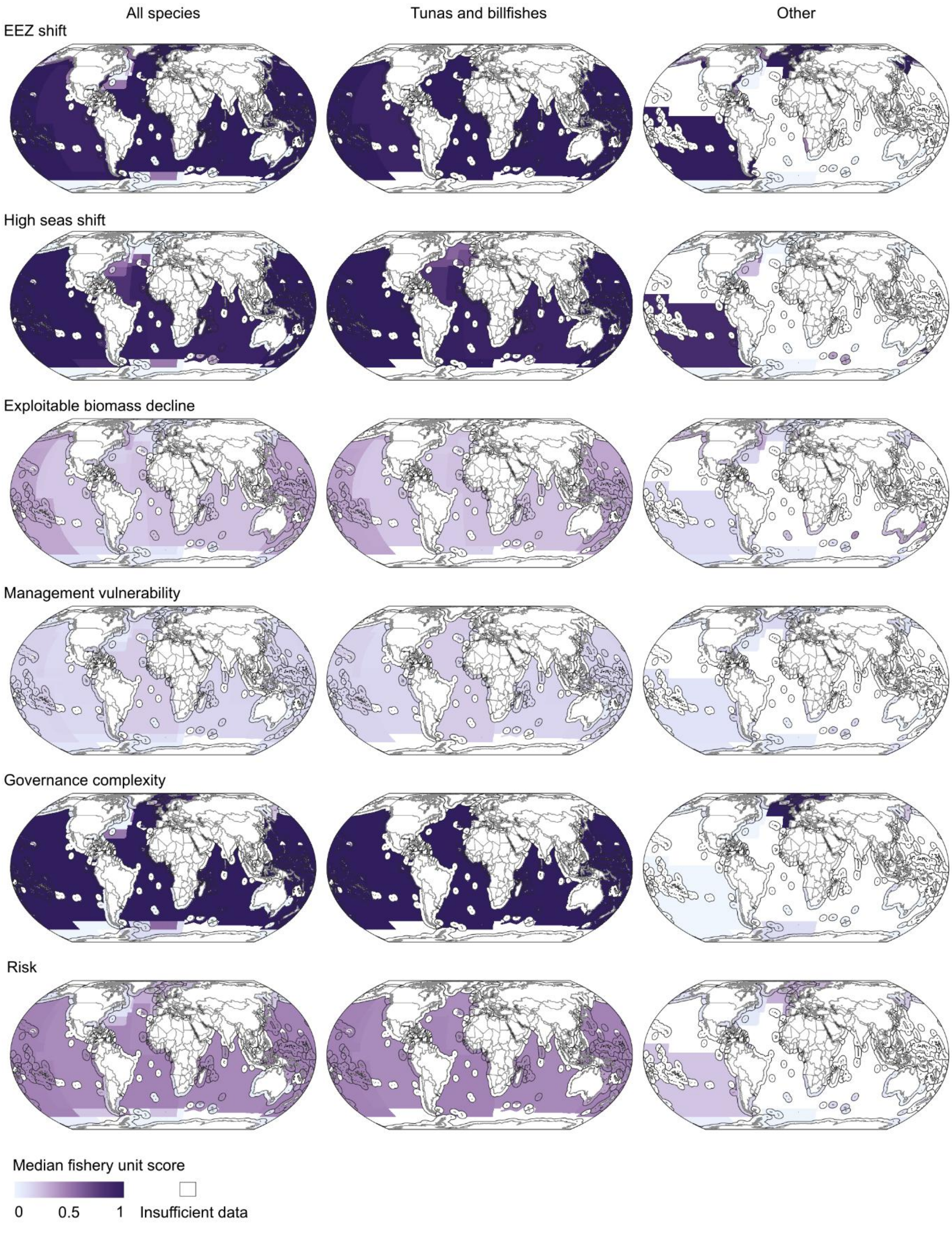


Figure S3. Median indicator values and overall risk across fishery units by fishery unit area*.* *Median across fishery units by fishery unit geographic operating area, by 0.5°x0.5° cell, and including exclusive economic zones boundaries for reference.*

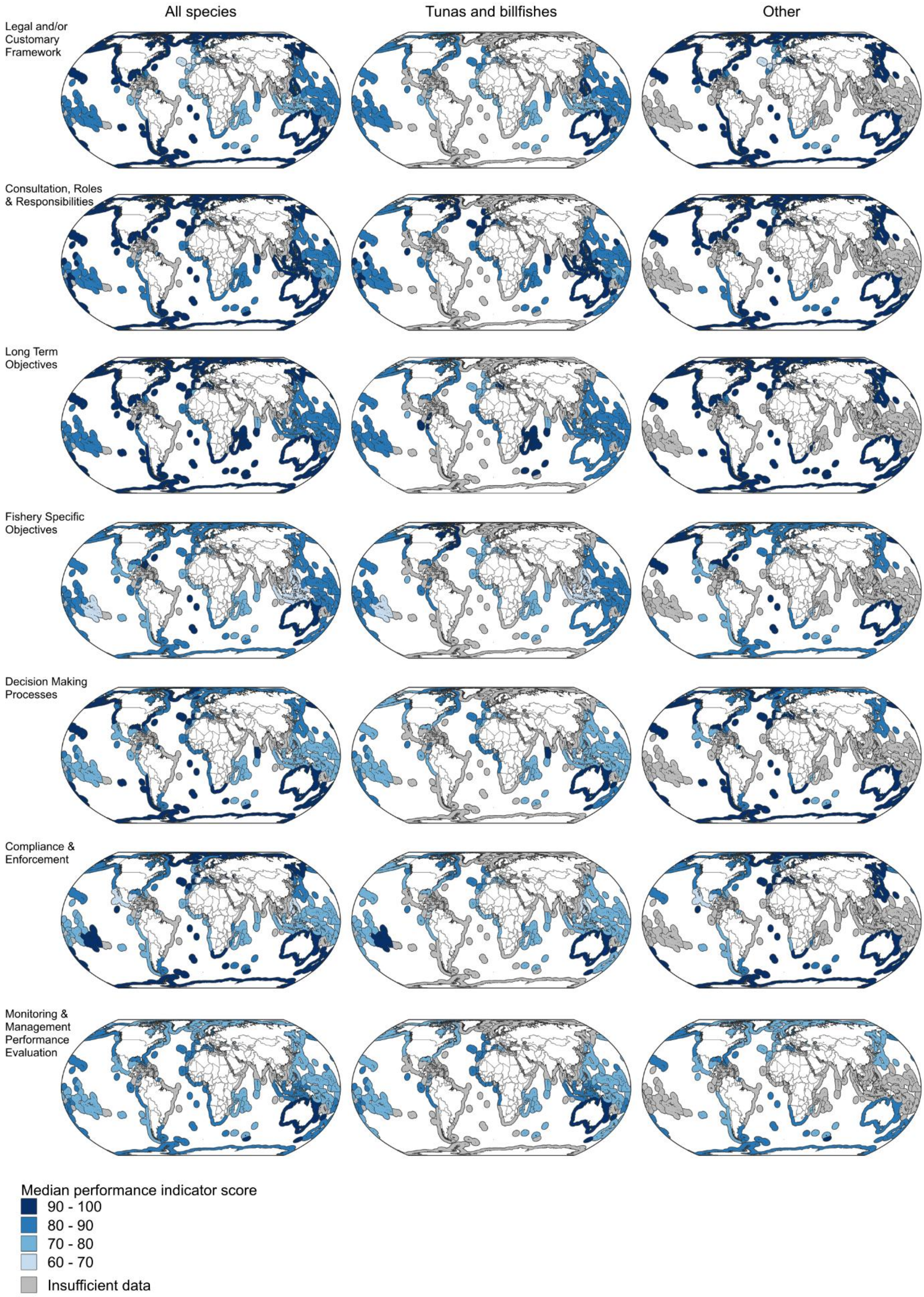


Figure S4. Median MSC assessment performance indicator score across fishery units estimated to be operating in each EEZ. *Exclusive economic zones (EEZs) exclude joint regimes,* *and data is separated by fishery units targeting tuna and billfish species versus those targeting other species. Individual fishery units may be assigned to more than on EEZ. The overall Principle 3 management effectiveness score is computed from the weighted average of the seven performance indicators shown. Fishery units scoring >60 in any performance indicator would have failed the MSC assessment and are not included.*

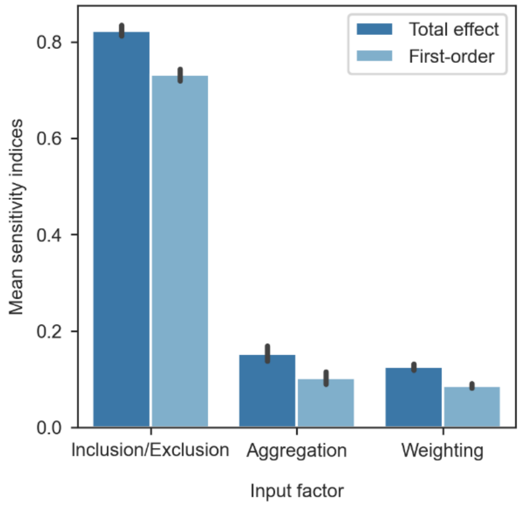


Figure S5. Mean Sobol' sensitivity indices across fishery units. *Influence of inclusion/exclusion of indicators, aggregation method (arithmetic versus geometric mean), and varying indicator weights on fishery unit risk variance calculated using a Sobol' sensitivity analysis. Mean first-order indices show the contribution of the individual input factor to the variance in risk averaged over all fishery units. Total effect shows the contribution of the input factor and all higher-order interactions (including interactions between factors) across factors, averaged over all fishery units. Whiskers show standard deviation around mean indices.*

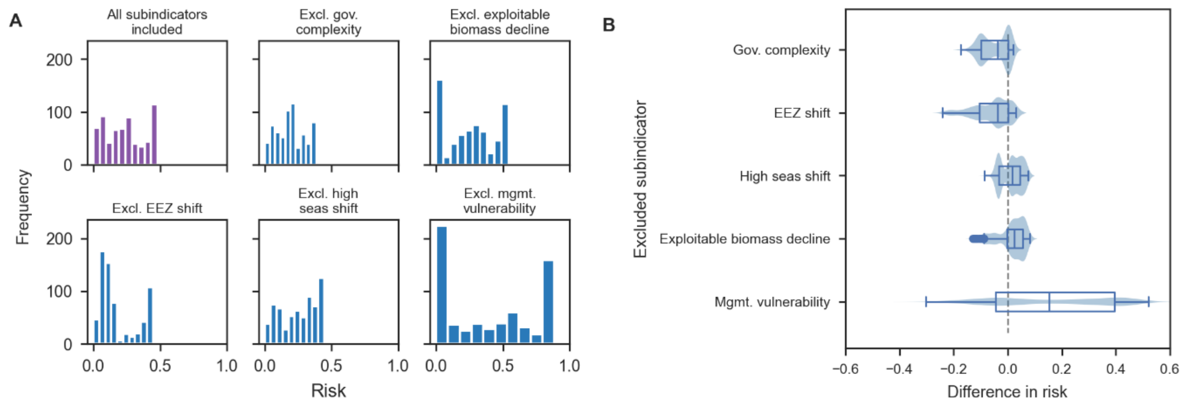


Figure S6. Sensitivity of risk values to excluding individual indicators from calculation. *A) Frequency distributions of risk values with all indicators included (top left panel, purple) or with a single indicator excluded from the calculated risk (other five panels, blue). B) Difference in risk between cases where a single indicator was excluded and where all indicators were included (single exclusion minus all included). Risk values were computed from Monte Carlo simulations for each fishery unit. Mgmt = Management.*

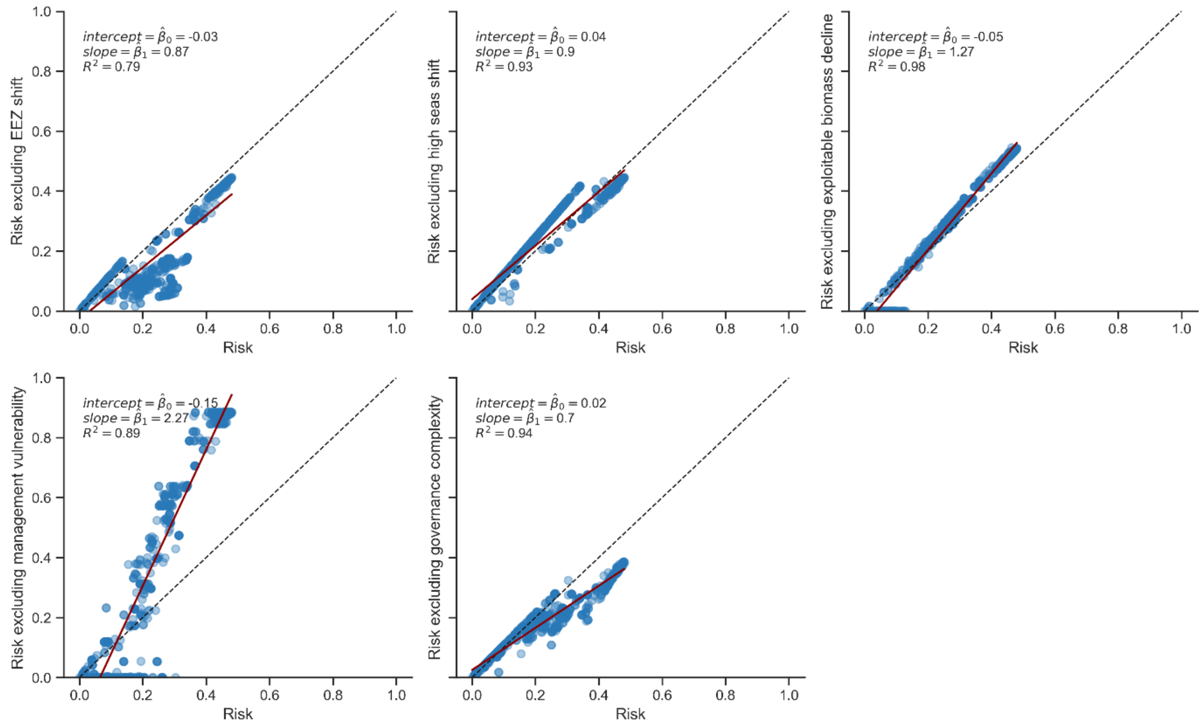


Figure S7. Regression of risk value with risk calculated with an indicator excluded. *Inclusion/exclusion sensitivity analysis results showing difference in risk for each fishery unit before and after excluding each indicator, one at a time.*

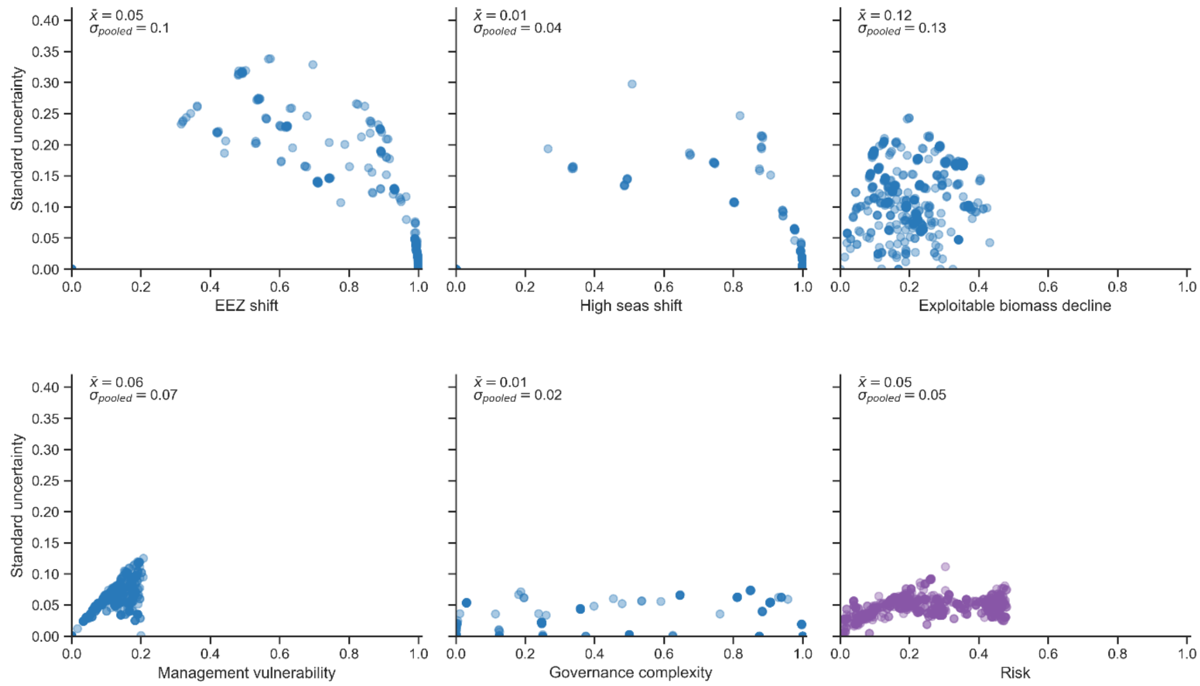


Figure S8. Standard uncertainty for each indicator, or overall risk, and fishery unit. *Standard uncertainty, measured by standard deviation across Monte Carlo simulations, for each fishery unit (points) and each indicator or overall risk. Panels show indicators of exposure (EEZ shift, high seas shift, exploitable biomass decline) or vulnerability (management vulnerability and governance complexity), and for risk overall. Also shown is mean standard uncertainty and pooled standard* *deviation (square root of arithmetic mean of squared standard deviation) across fishery units for each measure.*

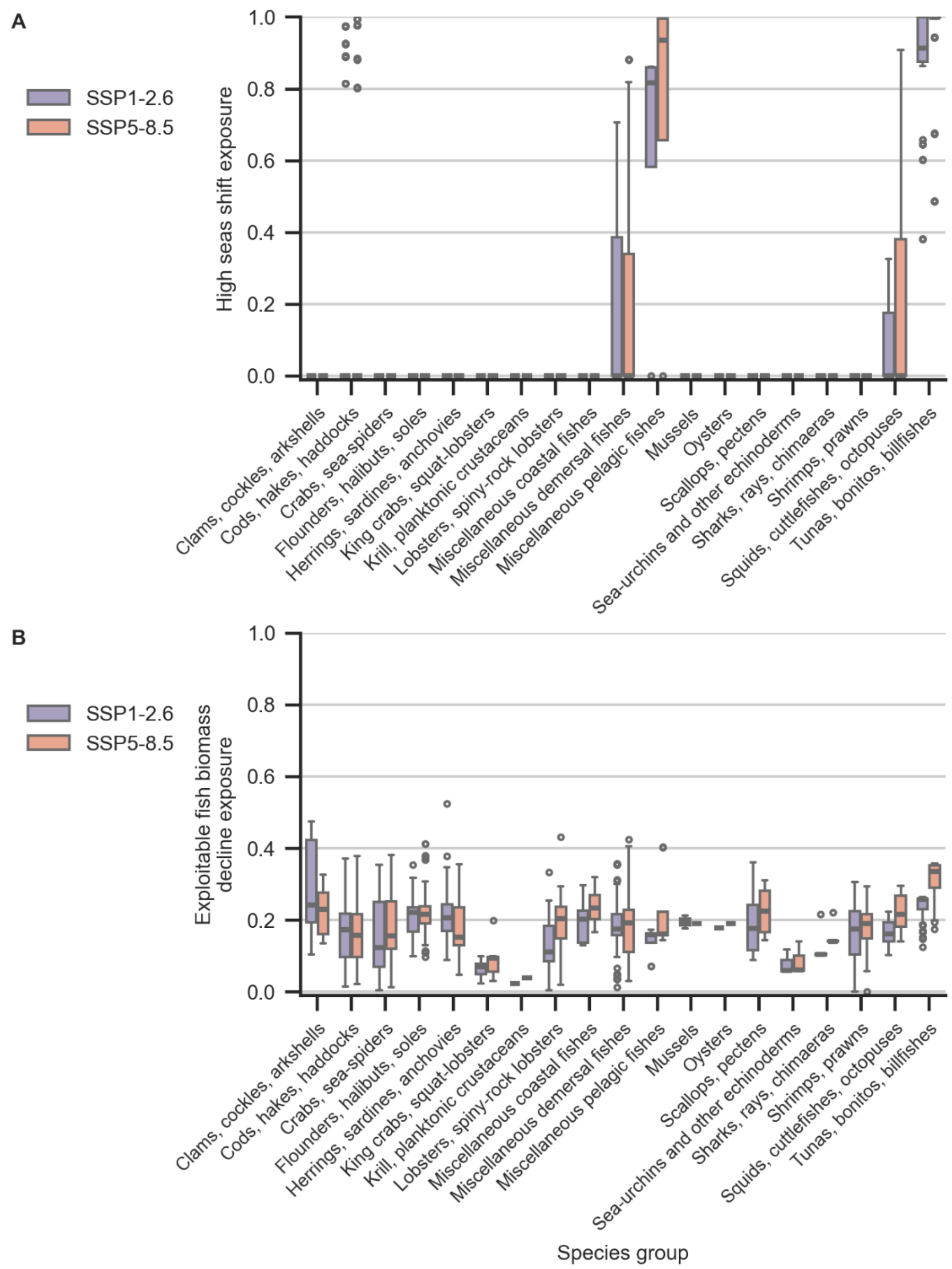


***Figure S9. Exposure indicator values under alternate climate change scenarios by species group.** A) High sea shift exposure and B) exploitable fish biomass decline exposure under shared socioeconomic pathway 5-8.5 (SSP5-8.5; red) compared to SSP1.2.6 (blue) for fishery units grouped by ISSCAAP species group. Exclusive economic zone shift exposure was not evaluated under alternate scenarios due to limitations in data availability. Boxes show interquartile range (IQR) and bold lines show median. Whiskers show lowest datum within Q1 − IQR × 1.5, and highest datum within Q3 + IQR × 1.5, while black open points show observations outside these fences.*

Table S1. Summary of measures used to compute indicators. *Indicators of exposure (EEZ shift, high seas shift, and exploitable biomass decline) show details on climate change projections. Projection details were not applicable to indicators of vulnerability (management vulnerability and governance complexity).*

Indicator	Measure	Rationale	Scenario	ESM	Historical Period	Mid-century period	Key References
EEZ shift	Mean relative change in stock share ratio between neighboring EEZ over stock area	Greater shifts of the stock distribution between neighboring national jurisdictions indicates greater exposure of the fishery to stock shift.	RCP8.5	CMIP5; GFDL	1951-2005	2041-2060	[1–5]
High seas shift	Mean relative change in stock share ratio between national jurisdictions and high seas over stock area	Greater shifts of the stock distribution between national jurisdictions and high seas indicates greater exposure of the fishery to stock shift.	SSP5-8.5	CMIP6; GFDL, IPSL, MPI	1951-2014	2041-2060	[4,5,22]
Exploitable biomass decline	Mean decrease in exploitable fish biomass over stock area	Greater decreases in exploitable biomass that the occur in the location of the target stock indicate greater exposure of the fishery to productivity decline.	SSP5-8.5	CMIP6; GFDL, IPSL	1951-2014	2041-2060	[6–8]
Management vulnerability	Inverse of weighted mean MSC Principle 3 management effectiveness score for fishery unit	Fishery units with lower Principle 3 scores are a proxy of MSC fishery units with fewer attributes needed to adapt to and recover from hazards, and are more likely to face management impacts potentially affecting stock health.					[9,10]
Governance complexity	Number of EEZ of stock geographic overlap	Chances of a successful, stable, cooperative management decision decreases with the number of parties involved, thus indicating higher vulnerability.					[11–13]

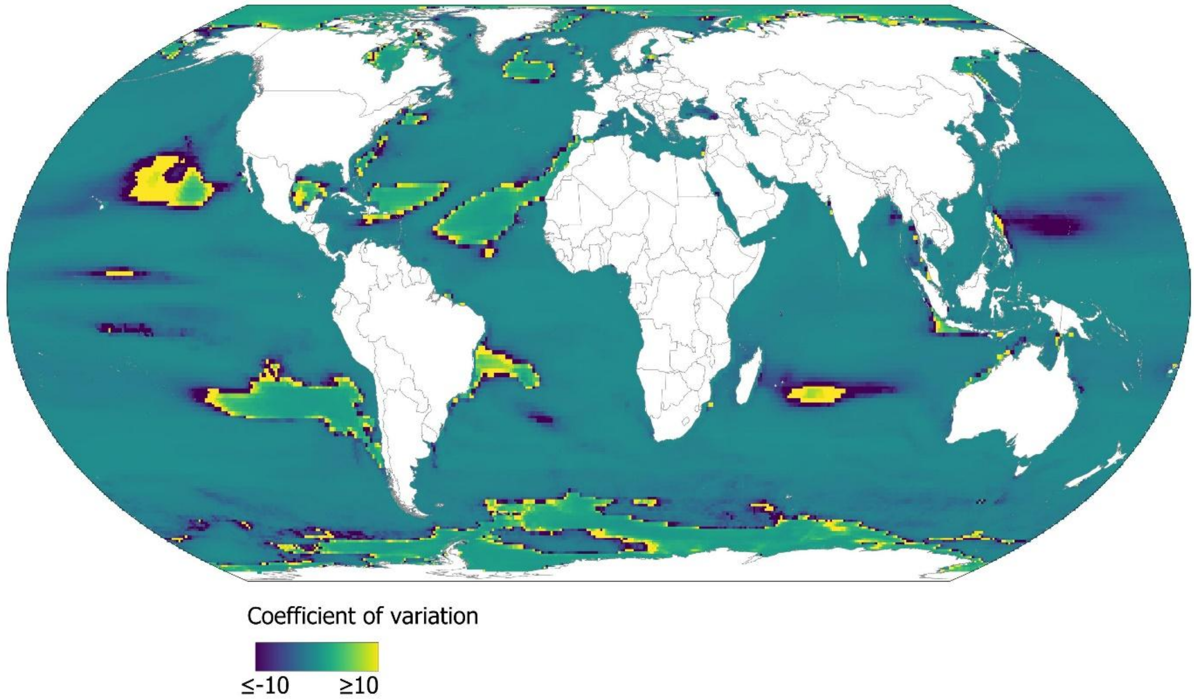


Figure S10. Coefficient of variation across the 10 ESM-model combinations for each cell.

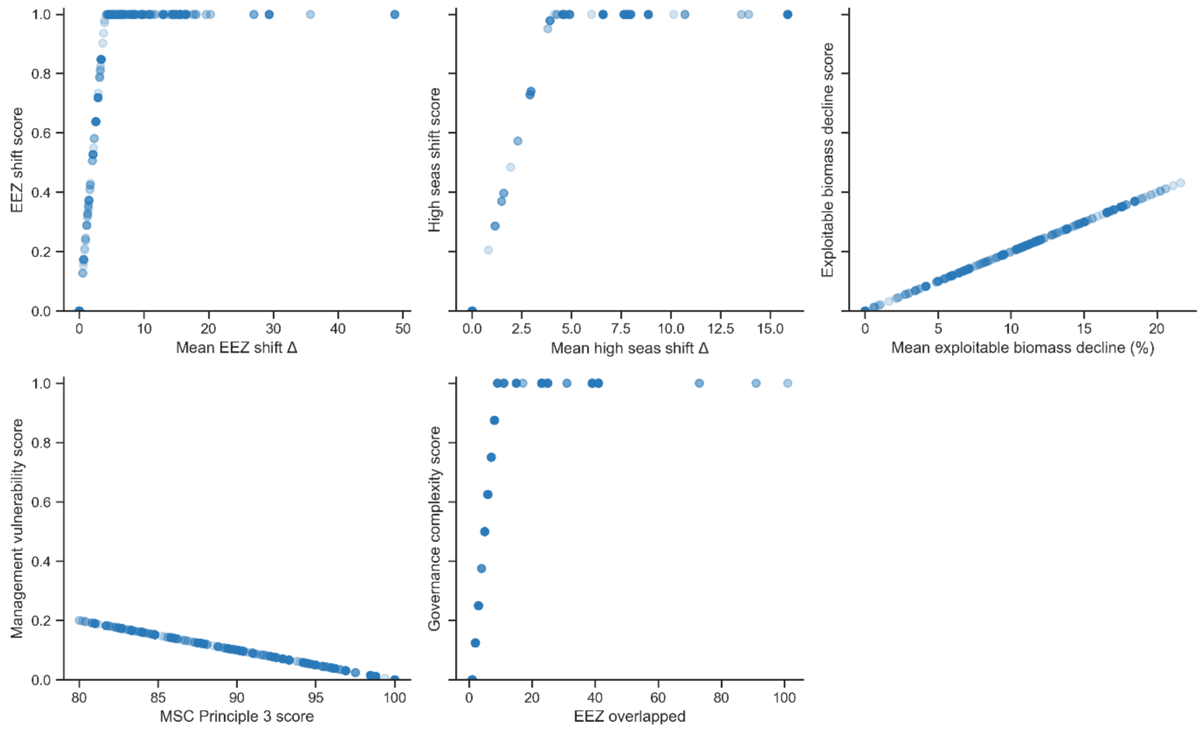


Figure S11. Indicator values versus dataset value*. Indicator values for each included fishery unit (points) before (x-axis) and after (y-axis) accounting for extreme values and rescaling from 0 to 1.*

Table S2. Sobol' sensitivity analysis input factors, with all inputs tested*. The input space was tested by varying the input factor with the possible variables using a uniform distribution, with each possible variable triggering a specific change in the input.*

Input factor	Variable	Tested input
Weighting	†0	All exposure indicators weighted evenly; Management vulnerability is 7/8 of vulnerability, governance complexity is 1/8 of vulnerability
	1	All exposure indicators weighted evenly; All vulnerability indicators weighted evenly
	2	Stock shifts (high seas and EEZ shift) each 1/4 of exposure, biomass decline 1/2 of exposure; All vulnerability indicators weighted evenly
	3	Stock shifts (high seas and EEZ shift) each 1/4 of exposure, biomass decline 1/2 of exposure; Management vulnerability is 7/8 of vulnerability, governance complexity is 1/8 of vulnerability
Inclusion/Exclusion	†0	Exclude nothing
	1	Exclude EEZ shift
	2	Exclude high seas shift
	3	Exclude exploitable biomass decline
	4	Exclude management vulnerability
	5	Exclude governance complexity
Aggregation	†0	Risk = sqrt(Exposure * Vulnerability)
	1	Risk = Exposure + Vulnerability /2

† Method implemented in final equation

Supplemental methods

Fishery units and fish stocks

The 661 fishery units evaluated included 637 with a 'certified' status and 24 with a 'suspended' status. Certified fisheries are those which have met MSC performance requirements and may be sold as MSC-certified. Suspended fisheries include those which were recently certified, but have fallen behind agreed timelines to improve certain criteria to remain certified, or have fallen below minimum performance requirements mid-assessment cycle[14]. If issues are remedied within the assessment cycle, the fishery may be audited and allowed to regain certification.

Each fishery unit was associated with its target stock in order to calculate stock-based indicator values (EEZ shift, high seas shift, biomass decline, and governance complexity). In most cases, each certified fishery unit targeted a single stock. However, five fishery units targeted two stocks each. In all of these, both stocks were neighboring stocks of the same species. For example, one fishery unit targeted the striped shrimp (*Pandalus montagui*) stock in Canada Shrimp Fishing Areas 2-3, and also targeted the striped shrimp stock in Canada Shrimp Fishing Area 4. In these cases, the two stocks were kept as separate geographic areas, with indicators measures computed for each of the stocks, then values for each stock were aggregated to get a single indicator value for the fishery unit.

Determining fisheries' exposure and vulnerability to hazards

EEZ stock shift indicator

We used published projections on the effects of climate change on the transboundary stock share ratio across neighbouring EEZs using a dynamic bioclimatic envelope model (DBEM)[2]. For each target stock of each fishery unit, we calculated Glass's delta (Δ) to compare projected mid-century stock share ratios between neighboring EEZ in 2041-2060 to modelled historical stock share ratios between the same neighboring EEZ in 1951-2005 to predict transboundary stock shift.

Changes in stock share ratio across neighboring EEZ were projected using DBEM extensively described in Cheung et al. 2010[15], 2016[16], 2016[17]. Oceanic conditions were driven by the Geophysical Fluid Dynamics Laboratory (GFDL) Earth system model following Representative Concentration Pathway 8.5 (RCP8.5)[2]. Stock share ratios were computed for each EEZ-neighbor pair (for example, between the United States and Canada EEZ-neighbor pair) for every species[2] using Sea Around Us EEZ boundaries[2,18].

In some cases, species were entirely not considered in Palacios-Abrantes et al.[2] due to being lesser known or less commercially important species (30 stocks of 20 species). In these cases, MSC experts on the fisheries targeting these stocks determined if there was a comparable species that was considered in Palacios-Abrantes et al.[2] based on current distribution in the stock area (including depth and latitudinal ranges) physiology, and habitat preference. Stock share data from the comparable species was then used as proxy.

In the projections, stocks were defined as individual transboundary stocks shared between neighboring EEZ. In other words, instead of defining stocks by species and population, they were defined by species and EEZ-neighbor pair. For example, a biological stock may be transboundary between three or more EEZ, but in the projections would be defined as a separate stock for each EEZ-neighbor pair. On the other hand, the stock assessed in an MSC assessment is defined at the community or population level, with the implication that a ‘stock’ is a biologically distinct unit[19]. Therefore, a single stock as assessed in an MSC assessment, which may overlap many EEZ, would be considered multiple individual transboundary stocks in the stock share projections, one stock for each EEZ-neighbor pair. To address this scale mismatch and estimate the exposure of the assessed stock of the fishery unit, we considered the stock shift between each EEZ-neighbor pair that matched in species and EEZ to the fishery unit’s assessed stock.

To discard neglectable stock contributions in EEZs due to limits in the resolution of the data, we focus stocks that overlap with EEZ areas at least 1% of the stock area, or at least 10% of the EEZ area. This was determined to adequately remove trivial overlaps by examining a sample against known information on the stock jurisdictions.

Shift between each EEZ-neighbor pair of the stock was calculated by Glass’s delta (Δ) effect size as described in the methods. The stock shift exposure of the assessed stock was then calculated as the average shift across all EEZ-neighbor pairs for the stock. In some cases, stocks were not considered to be transboundary in Palacios-Abrantes et al.[2] so no projections existed and an EEZ shift exposure of 0 was assigned, for example stocks overlapping island nations with no neighbors.

Related studies interpret a Glass’s delta of two as the threshold for a significant stock shift[2,22] since two equates to a very large effect with only a small portion of the two distributions overlapping[20,21]. Many values of mean EEZ shift Δ here fell beyond two (median Δ across all stocks was 1.31 and interquartile range (IQR) from 0 to 6.41), so in order to interpret a large Δ effect size as a fishery unit with significant exposure to EEZ shift, while also preserving as much variation between values as possible and avoiding extreme values overly dominating the scale, the highest exposure for EEZ shift was set as 4. In this way, a mean Δ for the targeted stock ≥2 would evaluate to an EEZ shift exposure for the fishery unit ≥0.5.

The mean shift values were then rescaled using a min-max scaler to limit values to between 0 and 1 to preserve overall data distribution. Final EEZ stock shift exposure values thus ranged from 0, no EEZ shift observed, to 1, mean EEZ shift Δ equal to 4 for the targeted stock. Note that exposure of 1 does not imply fully shift out an EEZ, but rather the largest observed mean shift.

Alternative measures of maximum shift and absolute shift were also considered, but not selected. Selecting to use only the single maximum shift for each stock may have theoretically given an indication of the area of most dramatic shift for the stock, but this measure is more sensitive to missing data, for which there were known cases, and limitations in the intended accuracy of shift projections on that scale by Palacios-Abrantes et al.[2]. Using absolute shift had similar limitations, as well as limiting the ability to compare across species with different annual variability patterns. For example, a stock that shifts 10% and has very high annual variability would be expected to have lower exposure than a second stock that shifts 10% but has very low annual variability. For these reasons, it was decided that averaging shifts between EEZ-pairs of the stock, and measuring in terms of historical standard deviations, would provide a more robust indication of exposure to stock shift.

High seas stock shift indicator

Similar to EEZ shift, projections from Palacios-Abrantes et al.[22] were used to compute the high seas shift measure using a Glass's delta (Δ) effect size for stocks identified as straddling. Projections estimated shifts between national jurisdictions and the high seas, such as could occur in stocks straddling the high seas. Biogeographic realms were used instead of individual EEZ to aggregate areas under national jurisdiction based on biologic similarity relevant to the distributions of straddling stocks[22]. More specifically, realms are regional classifications of global shelf areas based on biological characteristics[23,24]. There are twelve realms in total. For high seas, one of two delineations was used depending on the stock. For stocks that were identified as highly migratory, tuna RFMO (t-RFMO) high seas areas were used to disaggregate high seas areas in a way that is relevant to the management of these species[22]. For other stocks, the ocean basin identified adjacent to the realm was used to disaggregate high seas areas[22].

For each target stock of each fishery, we compared projected mid-century stock share ratios between ecological realms and neighboring high seas, delineated by t-RFMO areas of competence to modelled historical stock share ratios between the same areas in 1951-2014 to predict stock shift.

High seas stock share ratios were projected by Palacios-Abrantes et al.[22] similarly to EEZ stock share ratios[2], by projecting distributional changes of species between realms and t-RFMO or ocean basin high seas areas using a dynamic bioclimatic envelope model following SSP5-8.5[22]. For high seas shifts, the model was driven by three Earth system models (GFDL, IPSL, and MPIS) using the historical time period of 1951 to 2014, in line with the Coupled Model Intercomparison Project (CMIP) 6 protocol. Stock shift ratios were computed for each realm-high seas area (for example, between the Western Indo-Pacific realm and IOTC high seas area pair) of the species, and averaged over the three Earth system models[22]. The Commission for the Conservation of Southern Bluefin Tuna (CCSBT) area was excluded since there were no CCSBT stocks targeted by fisheries included in the dataset.

In the stock share projections, stocks were defined as individual straddling stocks by the species and each realm-high seas area pair which it crosses. Similar to EEZ shift, the stock assessed in an MSC assessment could overlap multiple individual stocks in the projection dataset. Similar to EEZ shift, a stock was only considered to have a presence in the high seas area (t-RFMO or ocean basin) or realm if the area of overlap was at least 1% of the stock area, or at least 10% of the high seas or realm area.

Each individual shift between realm-high seas area was calculated in same way as for EEZ shifts, using Glass's delta as described in the methods. The high seas stock shift exposure of the assessed stock was then calculated as the average shift of the subset of matching high seas area-realm pairs for the stock.

Similar to EEZ shifts, in cases where no high seas stock shares could be associated with the MSC fishery's stock, it was assumed the stock was not a straddling stock and therefore was assigned a high seas shift exposure of zero. Validation of a sample of stocks with missing high seas stock share data confirmed this was a reasonable assumption. In the included MSC fisheries, the highly migratory species of the tuna, bonitos, billfishes species group, as assigned in ISSCAAP (International Standard Statistical Classification of Aquatic Animals and Plants)[25], are the stocks that are commonly fished in the high seas where RFMO management is significant. Validation confirmed all stocks of this group were included in the high seas shifts.

Similar to EEZ shift, the maximum exposure high seas shift was set at $\Delta = 4$ to interpret a large Δ effect size as a fishery unit with significant exposure to high seas shift, while also preserving as much variation between values as possible. The mean high seas shift values were then rescaled using a min-max scaler to limit values to between 0 and 1 while preserving overall data distribution. Final high seas stock shift exposure values thus ranged from 0, no high seas shift observed, to 1, mean high seas shift Δ equal to 4 for the targeted stock.

Exploitable fish biomass decline indicator

We calculated the ensemble mean percent change in exploitable biomass across the ESM-models combinations for each cell, as is common[6,26,27], as in Eq. 1 where $\Delta_{tcb,m}$ is the change in total consumer biomass of size classes 10g to 100g for each model (m), and c is the ensemble mean for the cell.

$$c = \frac{1}{10}\sum_{m=1}^{10} \Delta_{tcb,m} \qquad \textit{Eq. 1}$$

The minimum exploitable fish biomass change observed across cells was -55.38%, and the maximum was 143.54% (mean -4.39, standard deviation ±21.31).

We then calculated the mean change across all cells touching the stock area to get average change in exploitable biomass in the geographic area of the stock, as in Eq. 2 where C' is the subset of ensemble means for each cell which the stock polygon touches, and $\bar{x}_{C'}$ is the mean change in total consumer biomass for the stock area.

$$\bar{x}_{C'} = \sum_{c \in C'}^{n} \frac{c}{|C'|} \qquad \textit{Eq. 2}$$

This was compared to the alternative method of including only cells where the centroid was within the stock area polygon. The centroid method resulted in many stock areas having missing data since smaller areas did not overlap any cell centroids. Further, the difference between these methods for areas which had results in both was minimal, so the all-touched method was selected to minimize missing data and enable all polygons to be treated the same.

Since we wanted to indicate exposure to decreases in exploitable biomass, any stock with a mean increase in biomass was reassigned a biomass decline of 0, as in Eq. 3, which would evaluate to an exposure of 0.

$$f(\bar{x}_{C'}) = \begin{cases} 0, & \bar{x}_{C'} \geq 0 \\ |\bar{x}_{C'}|, & \bar{x}_{C'} < 0 \end{cases} \qquad \textit{Eq. 3}$$

Values were rescaled using a min-max scaler to limit values between 0 and 1 while preserving overall data distribution. Final biomass decline exposure values thus ranged from 0, no exploitable fish biomass decline observed, to 1, maximum exploitable fish biomass decline (50% decline). A maximum of 50% was selected to align with related studies which interpret a change of ±50% to be very extreme events with a high potential for impacts to marine ecosystems and fisheries[6,8].

We calculated the Principle 3 score of each included fishery unit from the seven performance indicator scores, as reported in the certification report, to the nearest decimal, as is instructed by the MSC standard[14,28]. Some Principle 3 scores evaluated to slightly different than the score assigned by the auditor, with 20 fishery units evaluating to a score between 2.7 to 1 point different than the reported score. Upon inspection, this was most likely due to rounding inconsistencies by auditors in aggregating from performance indicator score to overall principle score, and would not have affected assessment outcome. For consistency, we chose to use calculated Principle 3 scores rather than the auditor scores.

In some cases, a single fishery received multiple Principle 3 scores due to variation in how assessments and scores have been reported. This occurred in 40 fishery units from 2 different reports. These cases were examined and since each fishery unit had two Principle 3 scores applied to them which were all within 0.7 points of each other, it was decided to use the mean of the two scores for the score of the fishery unit.

Min-max scaler was used to limit indicator values between 0 and 1, where the minimum was a score of 0 and maximum a score of 100, as in Eq. 6 where P is the Principle 3 score. Since we wanted to indicate higher vulnerability where a fishery has a lower Principle 3 score, we subtracted the scaled value from 1, as in Eq. 4, to get the management vulnerability indicator (M) where a value of 0 is a Principle 3 score of 100 and a value of 1 is a theoretical Principle 3 score of 0.

$$M = 1 - \frac{P}{100} \qquad \textit{Eq. 4}$$

In the Monte Carlo simulation for uncertainty, we used the uncertainty space across cells in the stock area, rather than across models for propagation of uncertainty. This was selected since sampling from uncertainty across models would have been too computationally intensive, and analysis supported variation across cells was significantly greater than average variation across models for each stock, evaluated using a paired t-test. To estimate variation across models for each stock, the mean coefficient of variation across models for each cell of the stock area was calculated. First, the coefficient of variation was calculated across the 10 ESM-model combinations for each cell, then mean coefficient of variation across the stock area was calculated. To estimate variation across the cells of the stock area (spatial variation), the coefficient of variation was calculated across the mean fishable biomass change of cells in the stock area. The paired t-test rejected the null hypothesis that the mean coefficient of variation across models for each cell in the stock area was greater than the coefficient of variation across mean fishable biomass change of cells in the stock area ($p < 0.05$).

Governance complexity indicator

The number of EEZs for each stock was calculated based on the number of EEZs which the stock geographically overlaps. In order to account for limitations in precision of EEZ and stock polygons, overlaps were only considered significant if the area of overlap was at least 1% of the stock area, or at least 10% of the EEZ area. In this way, we attempted to exclude overlaps caused only by imprecise boundary coordinates. This was determined to adequately remove trivial overlaps by examining a sample against known information on the stock jurisdictions. Unique EEZs were counted based on overlap with the Flanders Marine Institute EEZ from Marine Regions since these aligned best with political differentiations[29]. Joint regimes were excluded to avoid double counting since the nations under the joint regime agreement would be counted by overlap with their own jurisdiction. Overlapping claims however were included as unique jurisdictions since these areas do not fall under the same jurisdiction as the states claiming sovereignty and do not have finalized agreements[30]. An example of this is the Falkland / Malvinas Islands overlapping claim, claimed by both United Kingdom and Argentina, which would be counted separate from United Kingdom and Argentina. Territories were also considered separate from their sovereign since, although under the ultimate jurisdiction of their sovereign, have a degree of local government and decision making ability. For example Wallis and Fortuna would be considered separately from its sovereign, France.

Data were highly positively skewed, with some very extreme high outliers observed, generally from highly migratory tuna stocks. In order to avoid this small number of outliers from overly dominating the indicator scale, outliers were addressed using the interquartile range (IQR) method, where any value above the upper fence (third quartile plus 1.5 times the IQR) was considered extreme and reassigned the fence value. This resulted in any values above 9 being reassigned. The count of EEZ was then rescaled using a min-max scaler to limit values between 0 and 1.

Limitations exist for some stocks which are jointly managed by many nations which are not captured in this analysis. For example, stocks in waters of the European Union may be small in distribution, overlapping few EEZ, but are managed jointly by European Union member states. On the other hand, some may argue that stocks in the European Union which overlap many European Union countries should not be considered high vulnerability in this indicator because the European Union governs fisheries in its waters from under the umbrella of the European Union rather than individual countries. However, member countries still have the autonomy to disagree with management decisions, and as such still add to the complexity of coming to successful cooperative management decision.

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