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Targeting ocean conservation outcomes through threat reduction

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Nations have committed to reductions in the global rate of species extinctions through the Sustainable Development Goals 14 and 15, for ocean and terrestrial species, respectively. Biodiversity loss is worsening despite rapid growth in the number and extent of protected areas, both at sea and on land. Resolving this requires targeting the locations and actions that will deliver positive conservation outcomes for biodiversity. The Species Threat Abatement and Restoration (STAR) metric, developed by a consortium of experts, quantifies the contributions that abating threats and restoring habitats in specific places offer towards reducing extinction risk based on the IUCN Red List of Threatened Species™. STAR is now recommended as an appropriate metric by recent disclosure frameworks for companies to report their impacts on nature and STAR has seen widespread uptake within the private sector. However, it is currently only available for the terrestrial realm. We extend the coverage of the threat abatement component of the STAR metric ($STAR_T$), used to identify locations where positive interventions could make a large contribution to reducing global species extinction risk and where developments that increase threats to species should be mitigated, to the marine realm for 1646 marine species. Reducing unsustainable fishing provides the greatest opportunity to lower species extinction risk, comprising 43% of the marine $STAR_T$ score. Three-quarters (75%) of the global marine $STAR_T$ score falls entirely outside the boundaries of protected areas and only 2.7% falls within no-take protected areas. The STAR metric can be used both to guide protected area expansion and to target other actions, such as establishment and enforcement of fishing limits, to recover biodiversity.

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INTRODUCTION

While there has been recent growth in the fraction of the ocean within Marine Protected Areas, mirroring that on land, biodiversity loss continues to rise[1–3]. Part of the explanation for this is that designation often favours ease of establishment, through minimizing potential costs and conflicts, over the benefit to species and ecosystems and appropriate effective management practices[4,5]. If current trends continue, there is a real risk that recently adopted targets to increase the coverage of protected areas to 30% of the marine environment[6] may be met but without the necessary reduction in threat needed to halt declines, avoid extinctions, and recover species[7,8]. Effectively halting biodiversity loss requires quantifying how protected areas contribute to biodiversity conservation and targeting the specific actions which would deliver genuine benefits for biodiversity[2].

This challenge is particularly acute in the oceans. Marine ecosystems are heavily affected by human activities[4] and climate change impacts are accelerating and compounding the long-standing and poorly-managed consequences of overfishing, habitat loss, and pollution. Many megadiverse marine regions are under threat[9] and iconic marine megafauna, such as sharks and rays, marine mammals, albatrosses, and turtles are amongst the world's most threatened species groups[10,11]. The first estimates of marine extinction rates are at least one order of magnitude greater than the baseline rate of extinction seen in the fossil record and are now comparable to that of terrestrial vertebrates[11]. These marine extinction estimates caution that global political targets and commitments will not be met without a fundamental transformation of ocean conservation[12]. Threats can impact species in different ways[13] and identifying which threats, and their subsequent stressors, are important in specific areas is a prerequisite for applying effective conservation measures to prevent species extinctions and reduce biodiversity loss.

Biodiversity is often seen as challenging to measure by governments and non-state actors due to its inherent complexities. Major gaps remain in our knowledge, particularly in the marine environment[11]. While mentioned in policy goals, marine environments are often neglected due to low data availability and a lack of globally relevant metrics to measure impacts or progress towards targets[14]. This hinders efforts to improve accountability in marine environments and prevents the mainstreaming of responsibilities for mitigating and compensating for impacts to marine biodiversity throughout sectors and institutions. The production of appropriate marine biodiversity metrics and tools is therefore crucial to engage with and guide decision-makers, businesses, and civil society.

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The Kunming-Montreal Global Biodiversity Framework (GBF) has built momentum around a net positive outcomes goal to "bend back the curve" of biodiversity loss[6,15]. Goal A of the GBF commits countries to halt human-induced extinctions of known threatened species (including marine)[6]. The Sustainable Development Goals (SDGs) 14 and 15 have related targets, such as preventing the extinction of threatened species (target 15.5) and reducing threats to biodiversity by effectively regulating fisheries (target 14.4). Measuring progress towards these targets requires appropriate metrics. To mainstream biodiversity conservation across sectors and institutions, it is essential to be able to disaggregate responsibilities and add up contributions to meeting GBF and SDG targets at national and sub-national levels[16]. Cooperation across and beyond international borders is equally important for other global policy processes, such as the Biodiversity Beyond National Jurisdiction (BBNJ) treaty, to ensure the conservation and sustainable use of marine resources[17]. The Species Threat Abatement and Restoration (STAR)[18] metric, developed by the International Union for Conservation of Nature (IUCN) and a consortium of biodiversity experts from a range of academic, conservation, and private sector organizations, provides a spatially explicit metric to quantify the relative importance of mitigating different threats in different locations to reducing global extinction risk. This enables governments and other actors to prioritize actions, set targets, and measure progress towards species extinction risk goals.

The STAR metric uses integrated peer-reviewed data on species extinction risk as defined by the IUCN Red List Criteria[19], Area of Habitat (AOH) maps[20], and threats faced by species to quantify the relative contribution that threat-abatement actions taken in a particular place could make towards reducing species global extinction risk. The STAR metric is comprised of a threat abatement component ($STAR_T$), to identify areas where mitigating or removing threats could make a large contribution to reducing species extinction risk, and a restoration component ($STAR_R$), to identify areas where restoration activities could make a large contribution to reducing species extinction risk[18]. In principle, the global $STAR_T$ score represents the global threat abatement effort needed for all species to become Least Concern. $STAR_T$ scores can be disaggregated by threat, using data on the relative contribution of different threats to species extinction risk. It can also be disaggregated spatially, based on the current AOH of each species[18]. Quantifying how actions to reduce or remove threats from specific locations can benefit threatened species is required to set—and measure progress towards—science-based targets[18]. This will enable measurement of the degree to which goals in the post-2020 Global Biodiversity Framework are met, and to engage diverse actors in marine species conservation.

To date, the STAR metric has only been available for the terrestrial realm[18]. This paper presents the development of a threat abatement component of the Species Threat Abatement and Restoration (STAR) metric ($STAR_T$) for marine biodiversity to address this gap. The STAR metric has seen significant uptake by the private sector, where it is recommended as a suitable metric by disclosure frameworks such as the Science Based Targets Network (SBTN)[21] and the Taskforce on Nature-related Financial Disclosures (TNFD)[22]. As such, STAR is now a recognizable metric and used widely by corporates and financial institutions. It can be used to inform planning and action at multiple levels by identifying areas where the abatement of threats can contribute to reducing species extinctions and areas of biodiversity significance. A common and consistent STAR metric across terrestrial and marine environments will help businesses and governments consider, report and disclose on marine environments when they may have otherwise been omitted. We present and discuss the potential applications of marine $STAR_T$ and explore limitations and future research priorities.

RESULTS AND DISCUSSION

We included a total of 1646 species, assessed on the IUCN Red List of Threatened Species ™ as Near Threatened ($n = 498$) or threatened (Critically Endangered CR $n = 171$, Endangered EN $n = 293$, and Vulnerable VU, $n = 684$). These species span 11 classes, 62 orders, 192 families, and 552 genera and all trophic levels, ranging from functionally important foundation species such as corals and predatory megafaunal fishes to air-breathing turtles, mammals, and seabirds which disperse nutrients and connect multiple habitats and ecosystems. Most species (78%, $n = 1277$) were strictly marine, while 11% ($n = 184$) occur in marine and terrestrial realms, 4% ($n = 74$) in marine and freshwater realms, and 7% ($n = 111$) in all three realms. The groups with the greatest numbers of species in the analysis included sharks and rays ($n = 490$), reef-building corals ($n = 401$), bony-fishes ($n = 282$), birds ($n = 252$), and mammals ($n = 62$). See methods for the full list of taxa.

STAR threat-abatement scores ($STAR_T$), generated by summing the proportion of the Area of Habitat of each species, weighted by Red List category, in a grid cell, are presented for the entire surface of the planet at a resolution of 5 km × 5 km (Fig. 1). This score can be disaggregated by each threat in the IUCN Threat Classification Scheme[23], based upon the level to which a species is expected to be impacted (see Table 1), to quantify the contribution that abating threats in specific places offer towards reducing extinction risk (see Table 2). Marine $STAR_T$ scores ranged from 9.67^{-08} to 820.4 (per 5 km × 5 km grid cell) and are comparable with the range of terrestrial $STAR_T$ scores (1.26^{-07} to 836.2)[18]. For context, if the entirety of the range of a Critically Endangered species fell within a single 5 km × 5 km pixel, then a score of 400 would be assigned for that species alone.

The marine $STAR_T$ layer is comparable and complementary to the terrestrial version, using the same data sources and methodology to enable users of the metric to account for marine areas as well as terrestrial in their reporting and target-setting. As on land, most (95%) marine $STAR_T$ cells were classified in the "Very Low" $STAR_T$ category ($STAR_T$ 0–0.1 per 5 km × 5 km grid cell; Fig. 1), accounting collectively for only 20% of the global marine

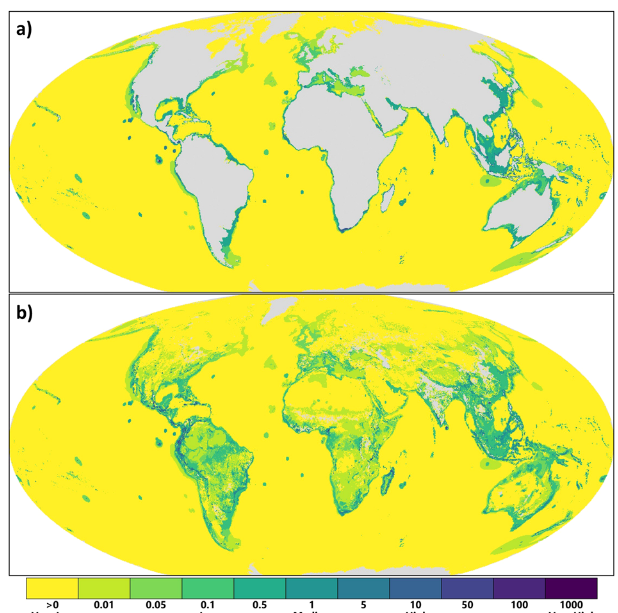

Fig. 1 Map of global $STAR_T$ scores. **a** A global marine $STAR_T$ layer; **b** a planet-wide[23] $STAR_T$ layer. Grid cell resolution is 5 km × 5 km. Gray areas have values of zero / no data. Categories[24]: Very Low (>0–0.1), Low (0.1–1), Medium (1–10), High (10–100), and Very High (>100).

Table 1. Expected percentage population decline over 10 years or three generations (from ref. [18]., based on work in ref. [60]) in relation to species scope and severity scores which are assigned during Red List assessments.

		Severity					
		Very Rapid Declines	Rapid Declines	Slow, Significant Declines	Causing/Could Cause Fluctuations	Negligible Declines	No Decline
Scope	Whole (>90%)	63	24	10	10	1	0
	Majority (50–90%)	52	18	9	9	0	0
	Minority (<50%)	24	7	5	5	0	0

Table 2. Schematic of how $STAR_T$ scores are calculated for an area of interest (AoI) based upon the species present, their IUCN Red List category, the proportion of their range in the AoI, and their potential impact from threats.

		Species 1	Species 2	Species 3	Species 4	Total $STAR_T$ Score (by threat)
	IUCN Red List Category	EN	VU	CR	NT	
	IUCN Red List Category Weighting	300	200	400	100	
	Proportion of range in AoI	0.2	0.15	0.1	0.05	
	Total $STAR_T$ Score for species in AoI	**60**	**30**	**40**	**5**	**135**
Threat A	Expected percentage population decline (%)	63	18	63	24	
	Proportion of species $STAR_T$ score attributed to Threat A in the AoI	0.75	0.29	0.51	0.16	
	$STAR_T$ Score for threat A in the AoI	**45.0**	**8.7**	**20.3**	**0.8**	**74.8**
Threat B	Expected percentage population decline (%)	10	24	9	63	
	Proportion of species $STAR_T$ score attributed to Threat B in the AoI	0.12	0.39	0.07	0.42	
	$STAR_T$ Score for threat B in the AoI	7.1	11.6	2.9	2.1	**23.8**
Threat C	Expected percentage population decline (%)	10	10	52	63	
	Proportion of species $STAR_T$ score attributed to Threat C in the AoI	0.12	0.16	0.42	0.42	
	$STAR_T$ Score for threat C in the AoI	**7.1**	**4.8**	**16.8**	**2.1**	**30.9**
Threat D	Expected percentage population decline (%)	1	10	0	0	
	Proportion of species $STAR_T$ score attributed to Threat D in the AoI	0.01	0.16	0.00	0.00	
	$STAR_T$ Score for threat D in the AoI	**0.7**	**4.8**	**0.0**	**0.0**	**5.6**
	Sum of expected percentage population decline (%) across all threats	84	62	124	150	

For each threat the expected population decline is identified based upon scope and severity scores (see Table 1 based on Mair et al.[18] and Garnett et al.[60]). For example, the total $STAR_T$ score for the hypothetical AoI below is 135 and is due to the presence of four species. Species 1 has a $STAR_T$ score of 60, which is the product of the IUCN Red List Category weighting for being Endangered (300) and the proportion of range within the AoI (0.2). For Threat A, Species 1 has an expected population decline of 63%, based on looking up the combination of Severity (very rapid declines) and Scope (across the whole (>90%) of the population in Table 1. For Threat B and C, Species 1 has an expected population decline of 10%, based on Severity (Slow, Significant Declines) and Scope (across the whole (>90%) of the population) in Table 1. Finally, For Threat D, Species 1 has an expected population decline of 1%, based on Severity (Negligible Declines) and Scope (across the whole (>90%) of the population) in Table 1. The $STAR_T$ score is then split proportionally across threats based on the sum of percentage population declines from all threats to that species. For species 1, the total summed population decline is 84 (63 for Threat A, 10 for Threat B, 10 for Threat C, and 1 for Threat D). Therefore the proportion of the $STAR_T$ score attributed to Threat A for Species 1 is 75% (63/84) of the total score, which would give a $STAR_T$ score for that specific threat of 45 (0.75×60). This can then be repeated for each species present within the AoI. We see here that the $STAR_T$ scores assigned to Threat A for the other three species are 8.7, 20.3, and 0.8 which gives a total $STAR_T$ score of 74.8 for this threat, which is 55% (74.8/135) of the $STAR_T$ score for the AoI.

conservation need and opportunity. Threat mitigation focused on a small fraction of the planet would have a disproportionate effect on reducing marine species extinction risk globally, with 0.001% of cells classified in the "Very High" category ($STAR_T > 100$ per 5 km $\times$ 5 km grid cell; 24 cells covering an area of 600 km^2) accounting for almost 2% of global $STAR_T$ scores. This pattern is typically driven by the presence of species with restricted ranges and / or where many threatened species ranges overlap[23].

Almost half (43%) of the total global marine $STAR_T$ score falls within the jurisdiction of ten countries (Fig. 2a). Indonesia has the greatest percentage of the global marine $STAR_T$ score (11.5%) within its Exclusive Economic Zone (EEZ), followed by Australia (6.9%), Mexico (4.1%), the Philippines (3.6%), Brazil (3.5%), and China (3.1%). The "high seas" or Areas Beyond National Jurisdiction (ABNJ) held a further 5.7% of the global marine $STAR_T$ score, however, this is spread across 42% of the global oceanic area. This is primarily due to higher species richness in more diverse coastal areas[24], as well as the relative size of the coastlines and EEZs of these countries. This is a similar pattern to that of terrestrial $STAR_T$ scores, where five countries contributed to 31.3% of the global

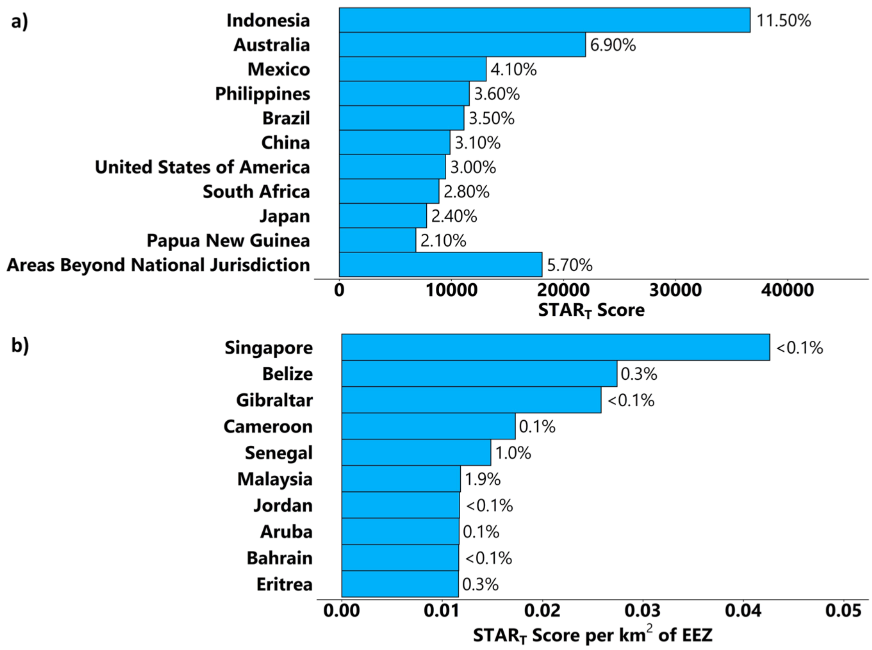

Fig. 2 Countries that contribute most to overall STAR$_T$ score and that have the highest STAR$_T$ densities. Top ten countries (and Areas Beyond National Jurisdiction) in terms of (**a**) total marine STAR$_T$ score, which include some of the largest countries and (**b**) marine STAR$_T$ score per km^2 of Exclusive Economic Zone area, where the highest STAR densities are found in smaller countries. Percentage of global scores within each country is also displayed.

STAR$_T$ score (Indonesia, Colombia, Mexico, Madagascar, and Brazil)[18]. It should also be noted that the ranges of many marine species span multiple jurisdictions and that threats in one jurisdiction may be dependent on the actions within others, so international cooperation to implement conservation actions to remove threats is particularly important in the marine environment.

It may also be informative to consider STAR$_T$ density to identify countries with smaller EEZs with particularly high STAR$_T$ scores per km^2 of EEZ (Fig. 2b). Singapore had a particularly high STAR$_T$ score per km^2, followed by Belize and Gibraltar. Singapore (710 km^2) and Gibraltar (390 km^2) have particularly small EEZs and are in biogeographical crossroads where marine biodiversity is high (see Large Marine Ecosystems (LME) below). Belize has a larger EEZ (34,300 km^2) but higher STAR$_T$ scores were driven by the presence of several Endangered and Critically Endangered taxa, including the restricted range Belizean Blue Hamlet (*Hypoplectrus maya*, EN), the endemic Social Wrasse (*Halichoeres socialis*, EN), and the Smalltooth Sawfish (*Pristis pectinata*, CR). The top 10 countries in terms of highest STAR$_T$ score per km^2 contributed only 3.7% of the global STAR$_T$ score.

Large Marine Ecosystems (LMEs) define broad areas of oceans based upon a range of ecological and oceanographic characteristics[25]. The Indonesian Sea LME (Fig. 3a) had the highest STAR$_T$ score (6% of the global total, 2,277,110 km^2) while the Canadian High Arctic - North Greenland LME had the lowest (0.0004% of the global score, 594,533 km^2). The highest STAR$_T$ scores per km^2 were in the Gulf of California LME (0.015 STAR$_T$ per km^2) followed by the East China Sea LME (0.011 STAR$_T$ per km^2). Arctic and Antarctic systems had the lowest STAR$_T$ scores in terms of both total and per unit area. This is likely due to the relatively low species richness and prevalence of human impacts (so few species are classed as threatened), as well as the relatively large geographic ranges of the species present. Only 25 threatened and Near-Threatened species occurred within Antarctica's waters, all of which had large ranges (mean: 100,579,448 km^2), which included 19 birds, five mammals, and the Porbeagle Shark (*Lamna nasus*).

Currently, one-quarter (24.9%) of the global marine STAR$_T$ score occurs within the boundaries of areas recorded in the World Database on Protected Areas (WDPA, 10.2% of the area covered by marine STAR)[26]. However, only 2.8% of the global marine STAR$_T$ score was within protected areas coded as no-take (or partially no-take). The establishment of effectively managed no-take marine protected areas is critical for meeting global goals to reduce extinction risk[27], especially given the contribution of fishing activities to the total marine STAR$_T$ score (Table 3). Cells with "High" (STAR$_T$ 10–100 per 5 km × 5 km grid cell) and "Very High" (STAR$_T$ > 100 per 5 km × 5 km grid cell) STAR$_T$ scores that fall outside of protected areas included areas in Taiwan (Fig. 3b) and Cabo Verde (Fig. 3c).

In addition to protected areas, there are other areas designated for biodiversity importance, 10.8% of the total marine STAR$_T$ score was in marine Key Biodiversity Areas[28] (KBAs, 4.2% of the area covered by marine STAR$_T$), 30.8% in Ecologically or Biologically Significant Marine Areas[29] (EBSAs, 21.2% of the area covered by marine STAR$_T$), and 17.1% in Important Marine Mammal Areas[30] (IMMAs, 4.0% of the area covered by marine STAR$_T$). As sites considered important by specialists for whales, dolphins, seals and sea cows, IMMAs account for a higher percentage (26.1%) of the global STAR$_T$ score for mammals specifically ($n = 42$). These results illustrate how the STAR$_T$ metric can complement other information sources for conservation planning.

Other threats included those relating to invasive species, climate change and severe weather, and pollution. The contribution of multiple threats within these classes to substantial proportions of the global STAR$_T$ score highlights that meeting global goals for marine biodiversity will require other management strategies, beyond a reliance on (no-take) protected areas alone. Studies have shown that climate change is a much larger threat to marine species than STAR scores suggest (13% of the global marine STAR$_T$)[31–33]. This is partly because the IUCN Red List identifies threats over the next ten years or three generations (whichever is longer). For some species, climate change will likely have substantial impacts, but over a longer time-frame. Hence, IUCN Red List assessments are likely to be a lagging indicator for

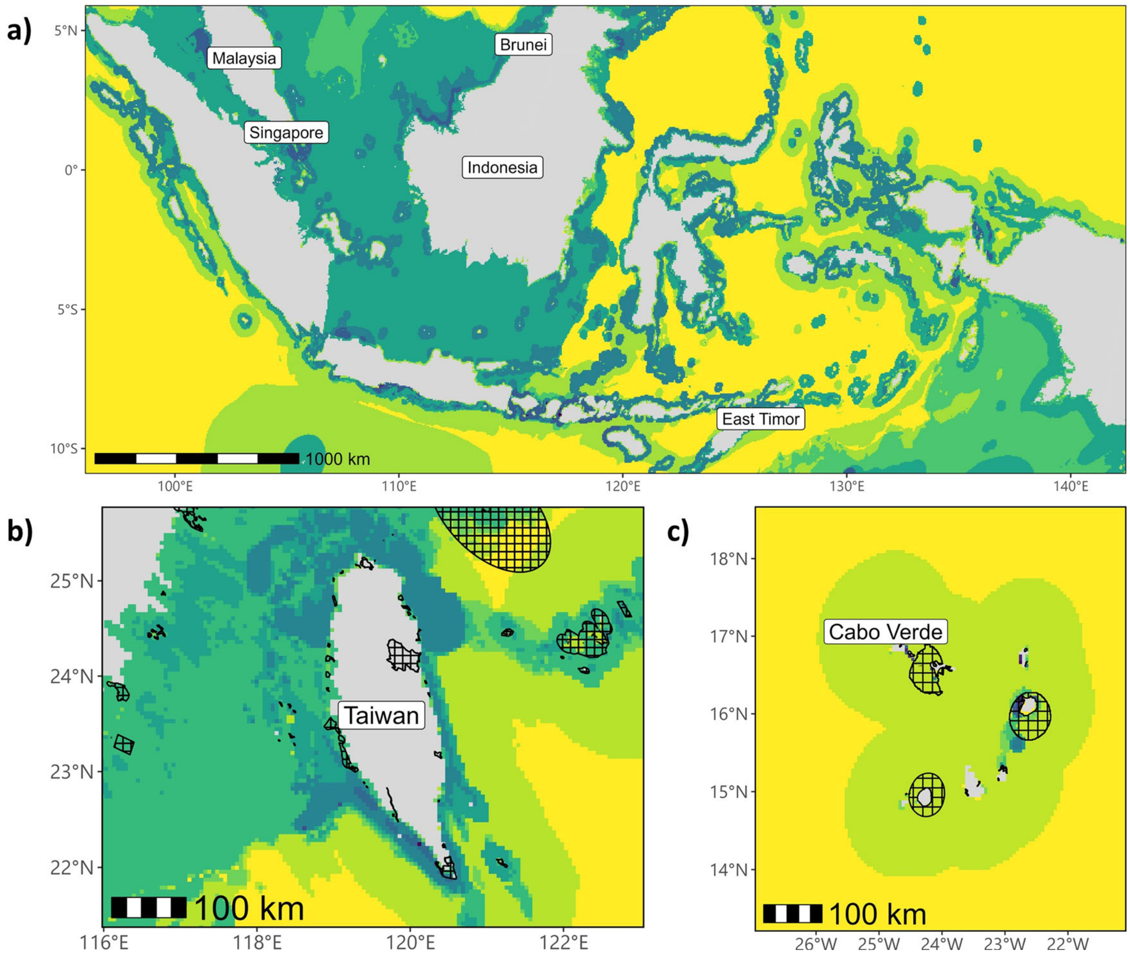

Fig. 3 Example areas of high STAR significance. STAR threat abatement ($STAR_T$) scores at 5 km × 5 km grid resolution for the marine environment in (**a**) the Indonesia Sea Large Marine Ecosystem, (**b**) Taiwan, and (**c**) Cabo Verde. Shading as per Fig. 1 for $STAR_T$ score categories. In (**b**) and (**c**) marine protected areas and Key Biodiversity Areas are shown using a black grid. Areas where marine $STAR_T$ scores are zero (mainly land, or no data) are presented in gray.

climate change impacts and so the use of STAR alone to assess these may not be appropriate as it may not capture the medium- and long-term severity of the accelerating impacts of climate change on species.

STAR on its own cannot meet every user's needs, but it does allow users to quickly identify which threats should be prioritized for 'ground truthing' and in which locations. Taking the example in Table 2, where four species are identified as potentially present at the site and are assessed to be impacted to differing degrees by each threat. In this example, Species 1 contributes most to the $STAR_T$ score due to a relatively high proportion of its range being within the area of interest and its EN status. When the $STAR_T$ score is split out by threats, we see that 75% of the area's $STAR_T$ score is attributed to Threat A. If Threat A is "Fishing & harvesting aquatic resources" then appropriate actions could focus on 'ground-truthing' and understanding fishing activities in the area with a view to managing them to reduce extinction risk. However, if Threat A is "Agricultural & forestry effluents" a ground-truthing approach to identify the source (upstream and in adjacent terrestrial areas) in order to reduce fertilizer usage may be more appropriate. If ground-truthing indicates that Threat A doesn't occur at the site, e.g., there are strict fisheries management plans and supporting data on fisheries catch / bycatch, then actions to address Threat C or Threat B can be considered next. The same applies to whether species are confirmed as present or not to identify potential priorities for that specific area of interest. Like many metrics, STAR relies on global datasets with varying sources of uncertainty (see Supplementary Table S1) that need in situ data and local knowledge to calibrate results on the ground. This $STAR_T$ layer can be used as a first step to identify potential priorities, alongside other appropriate metrics, in the marine environment where data and relevant metrics are sparse.

While the STAR metric can be disaggregated by threat, the spatial footprint of each threat is derived from the geographic range of the species; in other words, we make the assumption that each relevant threat is uniformly distributed across the species range. At present, variation in threat magnitude is currently not incorporated in the methodology and this is a key area for future development[18]. Efforts are ongoing to understand the footprint of major threatening processes in the oceans, particularly fisheries, habitat loss and climate change[13,34,35]. Data from 2013 showed that threats overlap with substantial portions of the ranges of marine species, where this overlap had increased by 37% when compared to 2008[13]. A decade on, if similar trends are followed, threats are likely to have intensified further across the ranges of species and potentially shifted in their distribution. These estimates of the distribution of threats, mainly based on models of industrial activity, such as fisheries catch[36,37] are now quite old, and efforts to update and improve these estimates will be required, particularly on the duration, frequency, and intensity of major threatening processes such as fishing. However, we caution that the spatial footprint of fishing and shipping activity is biased toward offshore industrial

Table 3. Percentage of global marine $STAR_T$ score for the ten threats in the IUCN Red List threat classification scheme[23,53] contributing most to the global $STAR_T$ score. A full list of threats can be found in the supplementary information.

Threat Code	Threat class	Threat Description	Percentage of global marine $STAR_T$ score (%)
5.4	Biological resource use: Fishing & harvesting aquatic resources	Harvesting aquatic wild animals or plants for commercial, recreation, subsistence, research, or cultural purposes, or for control/persecution reasons; includes accidental mortality/bycatch.	43.0%
8.1	Invasive & other problematic species, genes & diseases: Invasive non-native/alien species/ diseases	Harmful plants, animals, pathogens and other microbes not originally found within the ecosystem(s) in question and directly or indirectly introduced and spread into it by human activities.	5.4%
11.1	Climate change & severe weather: Habitat shifting & alteration	Major changes in habitat composition and location: sea-level rise, desertification, tundra thawing, coral bleaching,etc.	4.7%
11.3	Climate change & severe weather: Temperature extremes	Periods in which temperatures exceed or go below the normal range of variation: heat waves, cold spells, oceanic temperature changes, disappearance of glaciers/sea ice, etc.	4.6%
1.2	Residential & commercial development: Commercial & industrial areas	Factories and other commercial centers: military bases, factories, stand-alone shopping centres, office parks, power plants, train yards, ship yards, airports, landfills, etc.	4.5%
1.1	Residential & commercial development: Housing & urban areas	Human cities, towns, and settlements including non-housing development typically integrated with housing: urban areas, suburbs, villages, ranchettes, vacation homes, shopping areas, offices, schools, hospitals, birds flying into windows, land reclamation or expanding human habitation that causes habitat degradation in riverine, estuary and coastal areas, etc.	4.4%
9.2	Pollution: Industrial & military effluents	Water-borne pollutants from industrial and military sources including mining, energy production, and other resource extraction industries that include nutrients, toxic chemicals and/or sediments.	4.3%
9.1	Pollution: Domestic & urban waste water	Water-borne sewage and non-point runoff from housing and urban areas that include nutrients, toxic chemicals and/or sediments.	3.2%
1.3	Residential & commercial development: Tourism & recreation areas	Tourism and recreation sites with a substantial footprint: ski areas, golf courses, resorts, cricket fields, county parks, afghan goat polo fields, campgrounds, coastal and estuarine tourist resorts, etc.	2.9%
9.3	Pollution: Agricultural & forestry effluents	Water-borne pollutants from agricultural, silivicultural, and aquaculture systems that include nutrients, toxic chemicals and/or sediments including the effects of these pollutants on the site where they are applied.	2.8%
Total			79.8%

$STAR_T$ can be disaggregated by threat type, using information on the scope and severity of each threat documented in IUCN Red List assessments. Ten threats accounted for 80% of the global marine $STAR_T$ score (Table 3). Almost half (43.0%) of the global marine $STAR_T$ score is attributed to "Fishing & harvesting aquatic resources" which includes targeted fisheries and incidental captures (Table 3). This is consistent with other studies[13,71] and highlights the importance of appropriate fisheries management to prevent species extinctions.

vessels, overlooking the scale and impact of artisanal and subsistence fisheries[36,37]. Furthermore, threat information relating to fishing is primarily based on either catch or activity, which is only one component of risk and may give a biased assessment when used in isolation[38]; hence, we still need to develop spatial estimates of fishing mortality by species or size class. While areas could be prioritized by intersecting these imperfect human activity layers with species biodiversity or activity maps, this will ignore the threat status of a species and the degree to which taxa are susceptible to those threats[38]. Combining the STAR methodology with updated datasets to assess threats could fill an important gap in the future. Use of existing data on threats (such as Global Fishing Watch[39]) or existing studies that assess the footprint of threats[13,40] can offer options to mitigate and manage threats associated with larger-scale commercial activities, particularly on the high seas.

The STAR metric offers a first step in identifying the potentially important threats in an area where further information to "ground-truth" and "calibrate" the metric in terms of the threats and species that are actually present can be used to finalize conservation actions in an area. The calibration process for STAR, for a given area of interest, involves confirming the presence of species and the presence and impact of each threat. This should be done using locally relevant data and may include integrating spatial datasets with local knowledge. The estimated STAR scores for the area of interest are then updated to give calibrated STAR scores based on the species and species-threat combinations present.

Once calibrated, STAR can play a significant role in both Environmental Impact Assessments and Strategic Environmental Assessments, both of which are important for sectors such as energy and renewables[41,42]. Incorporating STAR into screening activities can aid companies in identifying suitable locations for infrastructure developments and appropriate mitigation measures, based on species-level threat information. Appropriate, national-level measures targeting potential threats from coastal and offshore developments, discharge of waste (including but not restricted to plastics), biosecurity to reduce the risk of invasive species spread, as well as global action against climate change, are required to reduce the impacts on marine species.

The STAR metric does not currently incorporate variation in species population densities or probability of occurrence. Clearly, a next stage is to develop more detailed AOH maps, ideally based on species distribution models which ideally would show important areas for particular species, such as breeding or nursery grounds and aggregation sites. The KBA assessment process[43] does identify such sites and KBA information can be used to provide additional context to the STAR layer. This does not preclude the need for more local data to be collected to inform decisions[44]. STAR can be "calibrated" by incorporating site-specific information on the species and threats that are present in an area to adjust $STAR_T$ scores[45]. Moreover, neither scientific processes to identify important sites for biodiversity in the marine realm (KBAs using quantitative data, and IMMAs largely using expert opinion), nor policy processes to describe them (EBSAs), have yet been comprehensively applied across regions and taxonomic groups, likely explaining the rather low total $STAR_T$ scores for such sites identified to date. This contrasts with KBAs on land, which have been more comprehensively identified, and account for nearly half of terrestrial STAR[18].

Our study analyzed data from a wide taxonomic diversity spanning 11 classes, 62 orders, 192 families, and 552 genera as well as a wide ecological diversity across all trophic levels from the top predators (sharks, rays, crocodiles, toothed whales) down to the habitat-forming foundation species (corals, mangroves), including invertebrates and air-breathing species that connect across realms. A total of 78% of species were strictly marine, while 12% also occur in terrestrial realms. However, the taxonomic coverage should be expanded in the future. Knowledge of marine species and their intrinsic sensitivity and exposure to threats will increase as further IUCN Red List assessments are completed and additional taxa are incorporated into STAR. The limited assessments of marine species are particularly pronounced for the deep sea and in ABNJ, due to their expanse and inaccessibility[46,47], and the impact of threats on many species remains unquantified and unassessed[48]. Even well-studied marine taxa such as bony-fishes have only around 60% of species assessed[10,49], and thus we were not able to include several fish families in the analysis. The STAR methodology does enable recalculation of the metric to incorporate additional groups when IUCN Red List assessments have been completed to help address these gaps in the future.

Ongoing updates to the marine and terrestrial $STAR_T$ metric will be important. Some species span different realms, including marine, terrestrial, and freshwater. The calculation of $STAR_T$ scores should be harmonized across terrestrial, marine, and freshwater realms. While the methods used here considered only the marine proportion of the AOH of each species, the harmonization of methods will allow us to better assess the proportion of a species AOH in each grid cell and prevent any double counting of species between realms. For the creation of the combined $STAR_T$ layer presented in this paper, the $STAR_T$ scores for species that were incorporated in the terrestrial $STAR_T$ layer were removed from all cells of the marine $STAR_T$ layer that overlapped between the two layers.

We did not consider the restoration component of the marine STAR metric ($STAR_R$) in this study to prioritize the creation of the $STAR_T$ layer to make it available for widespread usage. Time-series of remote sensing data are not available for marine habitats, meaning historical habitat extent, an essential requirement in the terrestrial STAR restoration calculation, cannot yet be determined. Restoration is less common in marine habitats compared with terrestrial, however, our knowledge of principles that can contribute to successful outcomes of restoration projects is increasing[50]. Marine biodiversity offsets or credits will likely play an important role in the future[51] and the development of a marine STAR restoration layer should be identified as a priority next step to help target areas where habitat restoration has the greatest potential to reduce species extinction risk.

We undertook an initial assessment of opportunities for reducing species extinction risk across the entirety of our planet. As such, STAR can act as a suitable metric by providing quantitative scores to guide and track actions towards goals to reduce marine species extinctions set out by political commitments including the Sustainable Development Goals 14 and 15, the BBNJ Agreement, and the post-2020 Global Biodiversity Framework. The development of this easy-to-use metric will help ensure that marine environments are not simply ignored during reporting or disclosures due to a lack of easily accessible information. Our finding that such a low percentage of the global marine $STAR_T$ falls within marine protected areas highlights the need to effectively place and design marine protected areas to halt the ongoing decline of ocean biodiversity. Disaggregation of $STAR_T$ scores by threat and geography can assist governments, the private sector, conservation organizations and other actors to identify and quantify where opportunities to change management practices and policy can deliver species extinction risk reduction. STAR scores can be calibrated through the verification of the presence of species, and the presence and severity of threats at the local level, in order to make the most appropriate decisions. Addressing the threats of overfishing and climate change will yield the greatest reduction in species extinction risk, so focus should rightly be placed on managing and mitigating these threats, which requires working both within and across national boundaries[13,52].

METHODS

The marine STAR Threat Abatement ($STAR_T$)[18] layer was created following a comparable procedure to that of the terrestrial $STAR_T$ to enable for them to be used in tandem. Deviations from this methodology, due to challenges of working in the marine environment, are documented. The main steps include: (1) the selection of species for inclusion; (2) refinement of species ranges based upon Area of Habitat (AOH), and (3) calculation of $STAR_T$ scores and disaggregation by threat. A summary of the data sources and potential uncertainties is provided in Supplementary Table S1. Throughout this paper the term "threat" is used as opposed to "stressor", the results of the threat, to align with Salafsky et al.[53]. and the IUCN Threat Classification Scheme[23] terminology.

Selection of species

The marine $STAR_T$ metric is calculated using the IUCN Red List of Threatened Species™ database and range maps for each species[10,54]. All species assessed as Near Threatened (NT) or threatened (Vulnerable, Endangered, or Critically Endangered) in the IUCN Red List in October 2022 were downloaded (51,467 species). Least Concern (LC) species are not included, as they are ultimately assigned a weighting of zero in the equation below and threats are not coded for the majority of these species. Data Deficient (DD) species were also excluded, as per the terrestrial methodology. While they may be threatened, DD species are too poorly understood to accurately classify their extinction risk as they often lack data on threats, habitats, and/or distribution[10,18]. This, however, may lead to some geographic biases in $STAR_T$ scores to regions that are better studied. This species list was then filtered to extract those coded by IUCN as occurring in marine habitats (2097 species, where the field "biome_marine" has the value of "TRUE") although they may also occur in other realms (terrestrial and/or freshwater).

All threatened and NT marine species within comprehensively assessed taxonomic groups (i.e., families or orders with at least 80% of species assessed in the IUCN Red List) were included (see Supplementary Table S3). This included all groups of species specifically named in the IUCN summary statistics tables[49] alongside the groups identified as comprehensively assessed from the Red List Application Programming Interface (API) to ensure all appropriate groups were included. This produced a list of 1698 species.

Version 2022.1 of the IUCN Red List range polygons was used for this study[10,54]. The IUCN Red List range dataset was filtered for the appropriate presence and origin codes, as per IUCN mapping standards guidance[55]. Polygons with the presence code of "Extant" (meaning the species is known or thought very likely to currently occur in the area) and "Possibly Extinct" (meaning the species is thought to have occurred in an area, but may now be extirpated from the area because of habitat loss and/or other threats) were selected alongside the origin codes of "Native", "Reintroduced", and "Assisted Colonization". This follows the same process applied in the terrestrial STAR paper[18]. Range polygons were available for 1694 species in the comprehensively assessed groups, meaning the four species lacking appropriate range polygon data were excluded.

Calculation of species Area of Habitat (AOH)

The AOH for each species was determined by creating a crosswalk between the habitat preferences documented against the IUCN Red List habitat classification scheme[56] with the Level 3 biomes of the IUCN Global Ecosystem Typology 2.0[57] as global raster layers are available for these habitats[58] (see Supplementary Data for details). All major and minor occurrences (coded within the Global Ecosystem Typology raster layers) of each biome were included for the purpose of producing the AOH layers. The crosswalk between the two typologies meant that separate rasters for each habitat, as per the Red list classification scheme, were created. This meant that if multiple habitats were marked as suitable in the Red List, then the rasters for those habitat types could be combined to produce the AOH area.

IUCN Red List range polygons[10,54] for the included species were converted to 5 km x 5 km resolution raster layers to match the resolution of the terrestrial STAR layer[18]. The values in each cell represented the proportion of the cell covered by the range. These values could then be divided by the total area of the range to derive the proportion of the total range in each cell. These species range rasters were overlain with the IUCN Level 3 Global Ecosystem Typology rasters[58]. Any portions of the range that fell outside of the extent of the habitats (identified through a crosswalk by aligning the habitat codes in the IUCN Red List with the Global Ecosystem Typology) marked as suitable habitat for that species in the IUCN Red List database were removed from the range. If the resulting species AOH was ≤5% of the species' original range polygon, then AOH was not used and the original range polygon was maintained. This was to ensure species were still included in the analysis, but that the $STAR_T$ scores of affected cells were not inflated by significantly reducing the range size. This occurred for 83 species (5%): 47 bony fish, 10 birds, 17 flowering plants, eight gastropods, and one cartilaginous fish. For 20 of these species (13 bony fish, six birds, and one gastropod) the AOH procedure reduced the range to zero. This could be linked to inaccuracies in the documentation of a species' habitat association, limitations in the crosswalk between habitats and the Global Ecosystem Typology, inaccuracies in mapping the habitats, or inaccuracies in the species' range.

When the information on the depth range of a species was available (20% of species), it was used to further refine the AOH for each species. Bathymetry data were obtained from the National Oceanic and Atmospheric Administration (NOAA)[59]. Any areas that fell outside of the minimum and maximum depth range of each species were excluded from species AOH. The shallowest maximum depth permitted was set at 100 m to ensure that ranges around oceanic islands were not substantially restricted given the resolution of the global depth layer and also account for potential inaccuracies in depth range information due to different sampling methodologies.

The proportion of the species' AOH was calculated for each grid cell by dividing the value of each grid cell by the total area of the AOH (calculated as 5 km × 5 km × proportion of cell covered by the AOH). The AOH layer was then cropped to areas that corresponded to the Global Ecosystem Typology level three biomes that are classified as marine to avoid significant overlap with the terrestrial STAR layer. This ensured that only the relevant proportion of a species' AOH was considered, particularly for species that (primarily) inhabit terrestrial and freshwater habitats.

Calculation of STAR threat-abatement ($STAR_T$) scores

The STAR threat abatement score ($STAR_T$) for a particular location (*i*) and threat (*t*) were calculated as per the terrestrial methodology to enable comparisons[18]:

$$T_{t,i} = \sum_{s}^{N_s} P_{s,i} W_s C_{s,t}$$

Where $P_{s,i}$ is the extent of current AOH of each species *s* within location *i* (expressed as a proportion of the global species' current AOH), W_s is the IUCN Red List category weight of species *s* (Near Threatened = 100; Vulnerable = 200; Endangered = 300; Critically Endangered = 400)[18]. *C* is the relative contribution of threat *t* to the extinction risk of species *s*, and *Ns* is the total number of species at location *i*. The scope (proportion of the total population affected) and severity (overall declines caused by the threat) of each threat to a species are documented during the Red List assessment process. The contribution of each threat (*C*) was determined based upon the expected percentage of population decline from these scope and severity scores. Each scope and severity category represents an estimated range (e.g., scope: Majority of population affected = 50–90%; severity: Rapid population declines = 20–30% over 10 years or three generations whichever is the longer; all scope and severity categories are presented in Table 1). Similarly to terrestrial STAR[18], there were differences in the numbers of species within each taxonomic class that had scope and severity scores coded (Supplementary Table 1). When scope and severity scores were known, the same procedure as terrestrial STAR[18], which was based on a detailed sensitivity analysis, was taken. Any "unknown" scores were assigned with the median of possible scores (median scope = "Majority (50–90%)"; median severity = "Slow, Significant Declines"). This covered 1234 species (75%). The percentage population decline scores used in ref. [18], (Table 1), from ref. [60], were assigned to species for each threat based upon the scope and severity scores. The values were calculated based upon birds and weighted to account for the impact of continuing threats based on their extent (i.e., the proportion of the total population affected) and their severity (i.e., the rate of population decline caused by the threat within its extent). Overall expected percentage population declines for each combination of scope and severity are presented in Table 1.

Scope and severity scores are recommended but are not mandatory for each Red List assessment. This meant that some groups were missing this information, however, relevant ongoing threats for these species were often coded as an overall threat score of three (Supplementary Table 1). As a result, for groups where the known scope and severity scores were 0% (Anthozoa, Hydrozoa, Liliopsida, Magnoliopsida, and Myxini) "unknown" scores were assigned with the median of possible scores (median scope = "Majority (50–90%)"; median severity = "Slow, Significant Declines"). This enabled these taxa to be included as relevant threats have been identified (albeit to a lesser level of detail) which then allowed for the percentage population decline scores to be identified as per ref. [18], (Table 1). This procedure was carried out for 430 species.

No threat information was available for 30 of the species that had spatial information so they were removed from the analysis. A further 18 species had negligible severity values across all threats, resulting in total population decline scores of zero, and so were also excluded. This left 1646 species, which was the final number of species included. Habitat preferences and threat information for each species was obtained from the IUCN Red List database using the "*rredlist*" R package[61].

Analysis of the STAR layer

The marine $STAR_T$ values formed a raster layer at 5×5 km resolution. The $STAR_T$ values were also disaggregated by each threat in the IUCN threat classification scheme[23]. Global statistics were then extracted for countries using a combination of the Natural Earth country boundaries (1:50 m scale)[62] and the Maritime Boundaries Geodatabase[63]. STAR values were also extracted for protected areas[26], Key Biodiversity Areas[28], Important Marine Mammal Areas (IMMAs)[30], and Large Marine Ecosystems[25]. Geospatial analyses were carried out in R Studio[64] using the packages "*terra*"[65], "*exactextractr*"[66], "tidyverse"[67], and "*sf*"[68].

Generation of $STAR_T$ map

As $STAR_T$ scores span several orders of magnitude, to enable the effective visualization of the $STAR_T$ layers values were classified from "very low" ($STAR_T$ 0–0.1 per 5 km grid cell) to "very high" ($STAR_T$ 100–1000 per 5 km grid cell) as per the categories applied in the IBAT business user guidance[45]. Global maps and maps of key regions were generated in R Studio[64] using the packages "*terra*"[65], "*tidyterra*"[69], "*rnaturalearth*"[62], and "*maptiles*"[70]. For the creation of the combined $STAR_T$ layer, the $STAR_T$ scores for all species that were present in the terrestrial $STAR_T$ layer were removed from all cells of the marine $STAR_T$ layer that overlapped between the two layers.

DATA AVAILABILITY

Species extinction risk categories, threat data, elevation limitations, habitat associations, and distribution polygons are publicly available under specified terms and conditions of use from the IUCN Red List website[10]. Key Biodiversity Area boundaries are available from the World Database of Key Biodiversity Areas[28] and Protected Area boundaries are available from the World Database of Protected Areas[26], again under specified terms and conditions of use. Natural Earth country boundaries (1:50 m scale)[62] are available online at www.naturalearthdata.com and EEZ shapefiles are available from the Maritime Boundaries Geodatabase[63] at www.marineregions.org. Spatial data are also available online for Large Marine Ecosystems[25] (https://www.lmehub.net/) and IMMAs[30] (https://www.marinemammalhabitat.org/immas/imma-spatial-layer-download/). Depth data is available at www.ncei.noaa.gov. Global $STAR_T$ scores at a grid cell resolution of 50×50 km are available in TIFF file format as Supplementary Data. The 5 km × 5 km layer will be made available in the Integrated Biodiversity Assessment Tool (IBAT).

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AUTHOR CONTRIBUTIONS

The study was conceptualized by J.A.T., A.S., M.S., L.B., L.M., T.B., N.K.D., F.H., and N.M. The STAR methodology was adapted by J.A.T. for this work. Data curation and formal analysis were carried out by J.A.T. with specific guidance from N.K.D., T.B., M.S., L.M., L.B., F.H., and A.S. Project administration was led by A.S. and supervised by M.S., L.B., T.B., and N.K.D. Visualization was led by J.A.T. with significant input from N.K.D. and F.H. Writing of the draft was led by J.A.T. with A.S., M.S., L.M., and L.B. Review and editing was led by N.K.D., T.B., and F.H. with significant input from B.P., S.B., K.C., R.W.J., M.E., and N.M.

COMPETING INTERESTS

All authors declare no competing interests.

ADDITIONAL INFORMATION

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