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Modelling the distribution of marine fishery resources: Where are we?

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Abstract

Ecological niche models (ENMs) and species distribution models (SDMs) have been widely applied to various studies relevant to biogeography, conservation biology, and ecology. These modelling techniques seek to develop spatial maps for projecting, among others past, current, and future species distributions. Born in the field of terrestrial ecology, only in recent years have these models been applied to marine environmental issues, especially to improve the forecasting of the distribution of occurrences and capturing of fishery resources. This study aimed to present through bibliometric analysis the characteristics of articles related to the use of ENMs and SDMs in marine fishery resources considering three main points: (1) state of the art: number of articles over the years, journals, countries, collaborations, and focus of research; (2) characteristics linked to fishery resources: marine biogeographic realms, taxonomic groups, life phases, oceanographic zones, and behaviours; (3) characteristics linked to methods: type of method, type of biological and, environmental data. We provide a list of 378 articles (derived from 930 screened ones), the results, and a discussion of our findings, which represent a baseline for the current status (strengths, limits, and gaps) of the interface between ENMs/SDMs and fishery resources.

KEYWORDS
bibliometric analysis, bioclimatic envelope models, catch, ecological niche, habitat suitability models, scientific production

1 | INTRODUCTION

Since the late 1990s, ecological niche models (ENMs) and species distribution models (SDMs) (among other terminologies, see Araújo & Peterson, 2012 and Guisan et al., 2013) have been widely applied in several studies relevant to biogeography, conservation biology, and ecology (Guisan et al., 2013; Robinson et al., 2011; Svenning et al., 2011). Although ENMs and SDMs are often synonymous in the literature, both terminologies are conceptually different: ENM refers to some estimation of the multidimensional environmental niches (E) (in the realm of niches, not distributions) used to outline areas (G) appropriate in terms of abiotic conditions (G_A), i.e. potential distribution of species (G_P). SDM needs to estimate the fundamental niche (N_F) – which allow some hypothesis of G_A – and, assessment of dispersal ability or movement (M), resulting in an occupied distributional area (G_O) ($G_O = G_A \cap M$) (Peterson & Soberón, 2012; Soberón

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et al., 2017; Soberón & Nakamura, 2009). Thus, ENM is correctly applied for current, future, and past potential distributional areas while SDMs are correctly applied exclusively for current distribution (Peterson & Soberón, 2012). However, both terms are many times applied interchangeably due to the similar algorithm, occurrence data, environmental variables, and capacity to produce maps (Peterson & Soberón, 2012) and for this reason will be called together as ENM/SDM from here on.

Correlative ENMs/SDMs are built using a modelling method that correlates known occurrence records of species observations (e.g., presence-only, presence-absence, abundance or biomass) and environmental information (abiotic or biotic) (Elith & Leathwick, 2009) partially linked to limiting factors or niche of species. The correlative ENMs/SDMs will generally identify some suite of environmental conditions that fall in between fundamental and realised niches, and the geographic area will be an intermediate between G_P and G_O (Peterson et al., 2015). The outputs of ENMs/SDMs have been used to predict the current and future potential distributions of invasive species (e.g., Barbosa, 2016; Cassemiro et al., 2018), identify priority areas for conservation (e.g., Lemes & Loyola, 2013; Nieto et al., 2017), infer the effects of global environmental change (e.g., climate change) on biodiversity (e.g., Gallardo et al., 2018; Martin et al., 2013), discuss biogeographic patterns (e.g., Werneck et al., 2012), and guide field research to find new populations or reintroductions (Chucholl, 2017), among others (see other applications in Peterson et al., 2011).

The growing use of ENMs/SDMs (Elith & Leathwick, 2009) reflects concerns about the effects of global environmental change on biodiversity, mainly anthropogenic climate change (Brotons, 2014), combined with the wide availability of open-access georeferenced species (e.g., Global Biodiversity Information Facility - GBIF, Distributed Information System for Biological Collections, and Ocean Biodiversity Information System - OBIS) and environmental databases (e.g., Bio-ORACLE, Assis et al., 2018; WorldClim, Fick & Hijmans, 2017; World Ocean Database, Levitus et al., 2013), methods (e.g., Merow et al., 2014; Martínez-Minaya et al., 2018; MaxEnt, Rangel & Loyola, 2012), software (e.g., R, Ahmed et al., 2015), and packages (e.g., R-INLA, Gómez-Rubio, 2020). Furthermore, numerous studies have identified and quantified the sources of methodological uncertainties (e.g., type of methods, type of environmental data) in ENMs/SDMs (Beale & Lennon, 2012; Heikkinen et al., 2006; Rocchini et al., 2011; Thibaud et al., 2014), as well as conceptual problems (Peterson & Soberón, 2012; Soberón, 2007, 2010; Soberón & Nakamura, 2009).

Fishery resources (species important to fisheries) contribute to an important portion of total animal protein consumption worldwide. For example, from a global perspective, the consumption rate increased by nearly double the annual growth of the world population (3.1% vs. 1.6%) from 1961 to 2017, higher than that of all other animal protein foods (meat, dairy, milk) (FAO, 2020). This growth rate requires better knowledge and results in rapidly increasing scientific output over the past three decades (1990–2020) and in emerging research fields (Xu et al., 2021). One of these fields includes ENMs/SDMs, which have been useful tools for understanding the dynamics in the distribution of species of commercial value and, consequently, to support their efficient and targeted management. Through ENMs/SDMs: (1) fisheries ecologists and biologists study the spatial and temporal distribution patterns of species (e.g., Pennino et al., 2022; Rufener et al., 2017), including attempts to consider the three-dimensionality of the marine environment (Bentlage et al., 2013; Duffy & Chown, 2017); (2) some computational software with automated modelling facilitates finding shoals by vessel captains (e.g., CatSat: https://www.catsat.com); and (3) more complex, dynamic, and multispecific models generate robust outputs allowing better decisions for managers (e.g., Coll et al., 2020).

Bibliometric analysis is a systematic approach used to quantitatively evaluate the scientific literature (Hood & Wilson, 2001) and research trends in a specific research field (Li et al., 2009). This kind of analysis is useful for deciphering and mapping the cumulative scientific knowledge and evolutionary nuances of well-established fields by making sense of large volumes of unstructured data in rigorous way (Donthu et al., 2021). When well done, bibliometric studies can build solid foundations for advancing a field in novel and meaningful ways providing such as: a general overview, knowledge gaps, and novel ideas for investigation (Donthu et al., 2021). In the field of ENMs/SDMs, bibliometric studies have been performed to quantify and characterize global (Barbosa & Schneck, 2015; Vaz et al., 2015) or specific geographic areas (e.g., Latin American scientific literature; Urbina-Cardona et al., 2019). The studies also covered different areas of research, such as for management purposes (Cayuela et al., 2009) and projecting invasive species distribution (Barbosa et al., 2012; Marcelino & Verbruggen, 2015; Silva et al., 2021). These studies showed a pattern of rapid growth in the number of publications, mainly in recent decades, following what is observed in reviews of ENMs/SDMs (Guisan et al., 2013; Melo-Merino et al., 2020; Pickens et al., 2021; Robinson et al., 2011, 2017; Svenning et al., 2011) as well as standards and guidelines to obtain

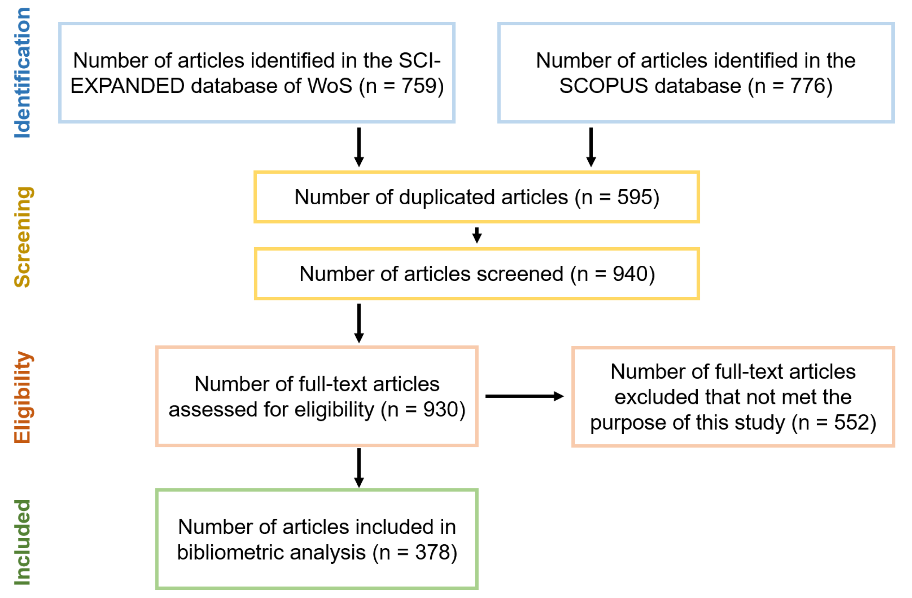

FIGURE 1 Flowchart of the PRISMA process for identifying articles on ENMs/SDMs in fishery resources.

better results when using correlative models (Araújo et al., 2019; Sillero et al., 2021; Zurell et al., 2020). Some systematic reviews and/or bibliometric studies have already been performed on ENMs/SDMs usage in marine environments (Melo-Merino et al., 2020; Pickens et al., 2021; Robinson et al., 2017). Robinson et al. (2017) and Melo-Merino et al. (2020) categorized 236 and 328 retained papers among marine biogeographic realms, taxonomic groups, methods applied, focus of research, among others. Furthermore, Robinson et al. (2017) perceived that 94% of studies failed to report properly uncertainty of data and model parameters and proposed recommendations for best practices in spatiotemporal modelling. Melo-Merino et al. (2020) explained the ecological niche concepts (based mainly in Soberón & Peterson, 2005 and Peterson & Soberón, 2012) and deeply discussed aspects of each aforementioned category. Through 225 retained articles, Pickens et al. (2021) focused their effort mainly on determining how data sources, statistics, and predictor variables differed among fish guilds. Although these three studies explored aspects such as publication growth over time and most studied biogeographic realms and taxonomic groups, the first two were more comprehensive, approaching all taxonomic groups in marine environment; the third was restricted to only marine fishes. Despite the bibliometric analyses done on ENMs/SDMs, none have specifically focused ENMs/SDMs connected to fishery resources.

Many questions arise when we think about using ENM/SDM to determine the distribution of species important to fisheries: When it started? Who publish? What taxon has been studied? To answer some of these questions, we conducted a bibliometric analysis to elucidate the aspects of articles applying ENMs/SDMs on fishery resources based on articles published in peer-reviewed journals indexed in the Science Citation Expanded - Web of Science and Scopus databases. Our main goals were: to (i) verify whether the number of scientific articles increased over the years, (ii) identify which journals and countries published these articles, (iii) verify the scientific collaboration between countries, and (iv) identify the focus of research. Additionally, we identified the most studied (v) marine biogeographic realms, (vi) taxonomic groups, (vii) life phases, (viii) oceanographic zones and (ix) behaviours for fishery resources, and finally identified the different (x) methods applied and (xi) types of biological and (xii) types of environmental data.

2 | MATERIAL AND METHODS

We used the Science Citation Index Expanded (SCI-EXPANDED) database of Clarivate Analytics Web of Science (WoS) and Scopus database to search the scientific literature on the use of ENMs and SDMs in fishery resources (updated on August 24, 2022). We conducted the search using a combination of two groups of terms inserted in the topic field option (i.e., title, abstract and author keywords, and keywords plus) from WoS and in 'paper title, abstract, and keywords' from Scopus. Inspired by Melo-Merino et al. (2020), the chosen terms were ("ecological niche model*" or "species distribution model*" or "habitat suitability model*" or "bioclimatic* envelope model*" or "habitat model*" or "spatial model*") and ("fishing resource*" or "fisheries resource*" or "fishery resource*" or "fishing" or "fisheries" or "fishery"). In our search only scientific articles (i.e., primary research articles) published in English until December 2021 were considered. The initial search resulted in a total number of 1535 articles, of which 759 were from the WoS and 776 were from Scopus databases. However, 595 were duplicated among the two databases, resulting in 940 articles after removal. We had no access to ten full-text articles and therefore they were excluded ("difficult-to-access journals will have to survive without our citations!"; Peterson & Soberón, 2012). Next, we manually revised each of the 930 articles to exclude the studies on ENMs/SDMs that did not meet the following criteria: (i) studies with species related to fisheries with commercial or recreational value (this criterion removed studies on corals, marine mammals, seabirds, sea turtles and, sponges), (ii) studies on species with total or partial life cycle living in marine environment (excluding lacustrine species), (iii) theoretical or methodological articles with at least one case study, (iv) studies in which the ENMs/SDMs were explicitly used to study the distribution of species, and (v) studies modelling the distribution of species (excluding the modelling distribution of fishery fleets). This step reduced our number of articles to 378 published between 1999 and 2021. This methodology followed the four phases (i.e., identification, screening, eligibility, and included) of the preferred reporting items for systematic review and meta-analyses (PRISMA) to select articles (Moher et al., 2009). The analytical framework (flowchart) of the methodology employed is illustrated in Figure 1. The list of selected articles is available in Appendix S1.

From each of the 378 articles, we extracted the following information: (i) year of publication, (ii) journal of publication, (iii) country of author(s), (iv) focus of research (6 levels e.g., current distribution, climate change), (v) biogeographic marine realm (13 levels; e.g., temperate northern Atlantic, southern ocean; based on Spalding et al., 2007), (vi) oceanographic zone in which the study was carried out (2 levels; estuarine/coastal, oceanic), (vii) behaviour of the studied species (7 levels; e.g., pelagic, reef-associated; based on Froese & Pauly, 2022), (viii) taxonomic group (7 levels; e.g., Actinopterygii, Crustacea), (ix) life phase investigated (2 levels; immature, adult), (x) methods used to generate the predictions (multiple levels; e.g., GLM, MaxEnt), (xi) type of biological data (6 levels; e.g., presence-only, presence-absence). Last, we classified by (xii) type of environmental data (3 levels) based on Soberón and Nakamura (2009) among abiotic (e.g., temperature, salinity), biotic$_{\text{non-interactive}}$ (biological variable which the presence of modelled species do not influence such variable; e.g., chlorophyll-a concentration) and biotic$_{\text{interactive}}$ (biological variable which the presence of modelled species influence such variable; e.g., competitor). For methods used, we also calculated if they were applied singly or under ensemble approach. Please see the detailed information of the aforementioned categories in Table 1 and discussion for definitions. If an article fit in more than one category, both categories were considered, and for this reason, the results were showed in proportion (%). Because some behaviours aspects change between estuarine/coastal and oceanic zones and focus of research or life phases vary between taxonomic groups, such results and discussions were combined.

Overall, the results were showed in map, barplots, dotplots, donut charts, radar charts, and tables in terms of number or frequency of articles. Additionally, we performed a scientific collaboration network between countries where nodes are countries and links are number of collaborations (Aria & Cuccurullo, 2017). All analyses and plots were developed in R (R Core Team, 2021) through the *ggplot2* v.3.3.5 (Wickham, 2016), and *bibliometrix* v.3.2.1 (Aria & Cuccurullo, 2017) packages.

3 | RESULTS

Overall, 378 articles were retained and included in this study. There has been an increasing number of articles since 1999 and a significant acceleration after 2010 (Figure 2). The articles by year reached a maximum of 81 articles in 2020. There were no articles published in 2004 on the list. Sixty-nine journals published studies linking ENMs/SDMs and fishery resources; however, only twenty journals accounted for 70% of articles (Table 2), and their impact factors (IFs) varied between 1.568 and 10.863, while the h-index varied between 33 and 332. From these published articles, 150 established a coauthorship with someone from a different country than the primary author, among the 35 countries across the 378 articles. The top-20 most frequent collaborator countries created three major groups centred in United States of America (USA) and European countries (Figure 3). Approximately half (49.9%) of the studies on the list focused their research on the current distribution of species followed by future predictions due to climate change (20.9%) and spatial distributions as a baseline for management issues (21%). Methodological, invasive species and past climates topics accounted for only 8% of articles (Table 3).

Among marine biogeographic realms, the Temperate Northern Atlantic and Temperate Northern Pacific were by far the most studied regions (Figure 4a). In fact, approximately half studies covered these two realms. At the other extreme, the Eastern Indo-Pacific, Temperate Southern Africa, Western Indo-Pacific, and Southern Ocean have fewer than fifteen published articles each (Figure 4a). Articles of ENMs/SDMs on adult Actinopterygii were the most frequent, comprising 51% of articles (Figure 4b). The following most frequent taxonomic groups included adult Elasmobranchii and Crustacea, comprising 19.8% and 12.2% articles, respectively. Surprisingly, the number of articles about the three Mollusca groups was very similar (6% ± 2). A total of 79% articles included organisms exclusively in their adult stage compared with 11% in immature stages (egg, larval, and juvenile) or both (10%) (Figure 4b). More studies were carried out in estuarine/coastal zones than in oceanic waters (Figure 4c). Moreover, studies in the estuarine/coastal zones comprised a larger diversity of behaviours, such as demersal, benthic, and reef-associated. In contrast, studies in oceanic zones were mostly restricted to pelagic and benthopelagic organisms (Figure 4c).

Fifty-nine applied methods were accounted (Appendix S2). The top-fourteen most popular methods were applied in approximately 86% of studies (Figure 5a), but we highlight the following methods: Generalized Additive (Mixed) Models (GAM), Maximum Entropy (MaxEnt), Generalized Linear (Mixed) Models (GLM), Boosted Regression Trees (BRT), and Random Forest (RF). GAM and GLM were used under frequentist and Bayesian inferences (Figure 5a). Thirty-five articles combined between two and eighteen methods under an ensemble approach (Figure 5a). From most popular, four methods were applied without ever being a part of any ensemble approach (Habitat Suitability Model, Dynamic Bioclimate Envelope Models, Arithmetic Mean Models, Geometric Mean Models), and five methods were only applied in an ensemble context (Artificial Neural Network, Multivariate Adaptive Regression Splines, Classification Tree Analysis, Flexible Discriminant Analysis, Surface Range Envelope) (Figure 5a). The most common biological data were presence-absence and catch

TABLE 1 Categories used in our bibliometric analysis for classification of studies on ENMs/SDMs in fishery resources

Biogeographic Marine Realm[a]	Taxonomic Group[b]	Life Phase[c]	Oceanographic Zone[d]	Behavior[e]	Applied Method[f]	Type of biological data[g]	Type of environmental data[h]	Focus of Research
Arctic	Actinopterygii	Adult	Estuarine/Coastal	Bathydemersal	ANN	Biomass	Abiotic-only	Climate Change
Temperate Northern Atlantic	Bivalvia	Immature	Oceanic	Bathypelagic	AMM	Catch rate	Abiotic + Biotic interactive	Current Distribution
Tropical Atlantic	Cephalopoda			Benthic	BRT	Count	Abiotic + Biotic non-interactive	Invasive Species
Temperate South America	Crustacea			Benthopelagic	CTA	Length		Management
Temperate Southern Africa	Gastropoda			Demersal	DBEM	Presence-Absence		Methodological
Western Indo-Pacific	Elasmobranchii			Pelagic	FDA	Presence-only		Past Climates
Temperate Northern Pacific	Combined commercial Species			Reef-associated	GAM (GAMM)			
Central Indo-Pacific					GLM (GLMM)			
Temperate Australasia					GMM			
Eastern Indo-Pacific					HSM			
Tropical Eastern Pacific					MARS			
Southern Ocean					MaxEnt			
Global					RF			
					SFE			
					Ensemble			
					Others			

Abbreviations: AMM, Arithmetic Mean Model; ANN, Artificial Neural Network; BRT, Boosted Regression Trees; CTA, Classification Tree Analysis; DBEM, Dynamic Bioclimate Envelope Models; FDA, Flexible Discriminant Analysis; GAM, Generalized Additive (Mixed) Models; GLM, Generalized Linear (Mixed) Models; GMM, Geometric Mean Model; HSM, Habitat Suitability Models; MARS, Multivariate Adaptive Regression Splines; MaxEnt, Maximum Entropy; RF, Random Forest; SRE, Surface Range Envelope.

[a]Based on Spalding et al. (2007).

[b]Combined commercial species: more than one specie combined in a single index.

[c]Immature: egg, larval, juvenile.

[d]Estuarine/coastal: studies developed over the continental shelves; Oceanic: otherwise.

[e]Based on Froese and Pauly (2022).

[f]GAM and GLM: frequentist or Bayesian inference; Ensemble: more than one method combined; see list of Others in Appendix S2.

[g]Count: number of individuals (abundance) or species; Biomass: weight; Catch rate: Catch-per-unit-effort (CPUE or similar e.g., NPUE, BPUE); articles under hurdle approach were categorized in more than one category (e.g. presence-absence and count/catch rate).

[h]Based on Soberón and Nakamura (2009), see Discussion for definitions.

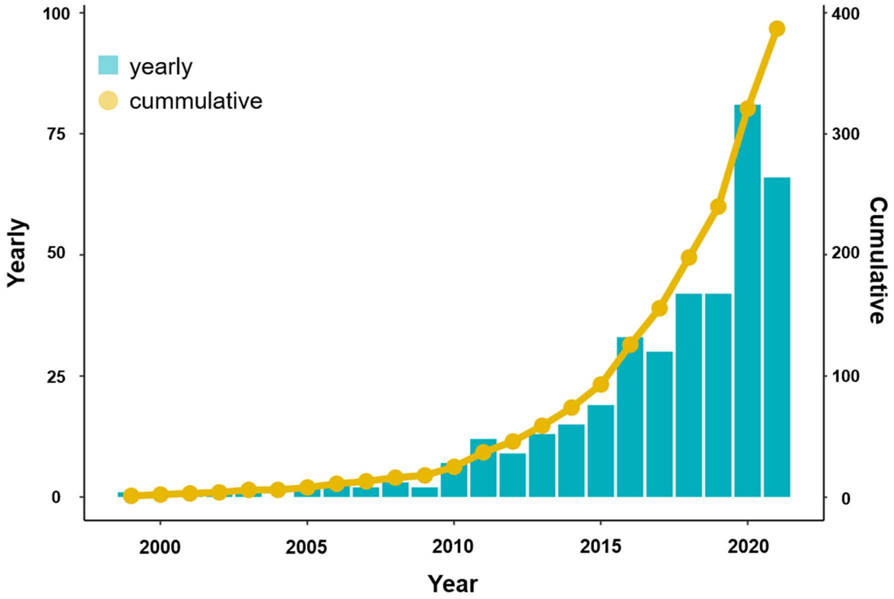

FIGURE 2 Yearly and cumulative number of articles on ENMs/SDMs in fishery resources until December 2021 indexed in the Web of Science and Scopus databases.

TABLE 2 Top-20 journals (plus impact factor and h-index) that published articles on ENMs/SDMs in fishery resources until December 2021 indexed in the Web of Science and Scopus databases

Journal	Number of articles	IF[a]	h-index
ICES Journal of Marine Science	32	3.593	117
Frontiers in Marine Science	26	4.435	49
Fisheries Oceanography	25	2.422	94
Fisheries Research	17	2.422	94
Marine Ecology Progress Series	16	2.359	188
Plos One	16	3.24	332
Canadian Journal of Fisheries and aquatic Sciences	13	2.46	153
Hydrobiologia	12	2.385	141
Diversity and Distributions	11	4.092	118
Deep-Sea Research Part II - Topical Studies in Oceanography	8	2.732	140
Ecological Modelling	8	2.93	156
Journal of Sea Research	8	2.108	81
Ecological Applications	7	4.252	213
Ecology and Evolution	7	2.91	63
Global Change Biology	7	10.863	255
Journal of Marine Systems	6	2.96	109
Marine and Coastal Fisheries	6	1.568	33
Progress in Oceanography	6	3.81	132
Estuarine, Coastal and Shelf Science	5	2.929	134
Marine Policy	5	4.315	104

[a]Impact Factor of 2021 (JCR).

rate (catch-per-unit-effort; CPUE or similar e.g., NPUE, BPUE) followed by presence-only, which combined accounted for 80% of input data (Figure 5b). Considering the environmental data, 45% and 42% of articles used abiotic-only or abiotic plus noninteractive biotic variables, respectively (Figure 5c). Only 13% used abiotic plus interactive biotic variables (Figure 5c), and none exclusively used interactive biotic variables.

4 | DISCUSSION

4.1 | State of the art

Our bibliometric analysis revealed an increasing number of articles published between 1999 and 2021, especially after 2010. The acceleration in use of these models in fishery resources

FIGURE 3 Top-20 country collaboration network publishing on ENMs/SDMs in fishery resources. Size of nodes and links are number of articles and collaborations of countries, respectively. Arrangement of intragroup (coloured) and intergroup (grey) are generated by commonness of collaborations.

TABLE 3 Number of studies among the taxonomic groups and focus of research publishing about ENMs/SDMs in fishery resources

	Focus of Research					
Taxonomic group	Current distribution	Climate change	Management	Methodological	Invasive species	Past climates
Actinopterygii	163	52	66	18	1	2
Elasmobranchii	56	18	26	8		
Crustacea	27	13	7	5		
Bivalvia	10	10	6	1	3	
Cephalopoda	19	10	8	3		
Gastropoda	4	10	2	1	2	
Combined commercial species	5	6	5	2		

Note: The frequency may be based in counts larger than the total amount of retained articles (378) due to the possibility of multiple fitting among categories.

(2010) occurred a few years after compared with more comprehensive studies in marine environments (2005) (Melo-Merino et al., 2020; Robinson et al., 2017). This growing use of ENMs/SDMs is expected, as they can generate good insights of distribution or abundance of a resource (depending on the nature of the input data), in view of the inherent sampling difficulties in the marine environment. Compared with the mainland, wide zones of oceans remains unexplored. In fact, there are few studies based on fishery-independent sampling (Pennino et al., 2019), which makes observations in many instances dependent on fisheries (e.g., Lezama-Ochoa et al., 2020; Rezende et al., 2019; Rufener et al., 2017). In many countries, fishery data are the only source available to scientists, which requires their careful and validated use due to its commercially-driven nature, resulting in possible distribution bias (i.e., preferential sampling) (Alglave et al., 2022; Rufener et al., 2021). Despite this point, when properly used, fishery data become an important and necessary source and, coupled to ENMs/SDMs, could provide a good understanding of the dynamics in distribution of fisheries resources (Pennino et al., 2016). In the terrestrial environment, larger human accessibility, lower cost, and the possibility of nonscientific observations seem to be the main reasons for the discrepancy between the two environments (but see citizen science by Ver Hoef et al., 2021). The growing number of articles is also related

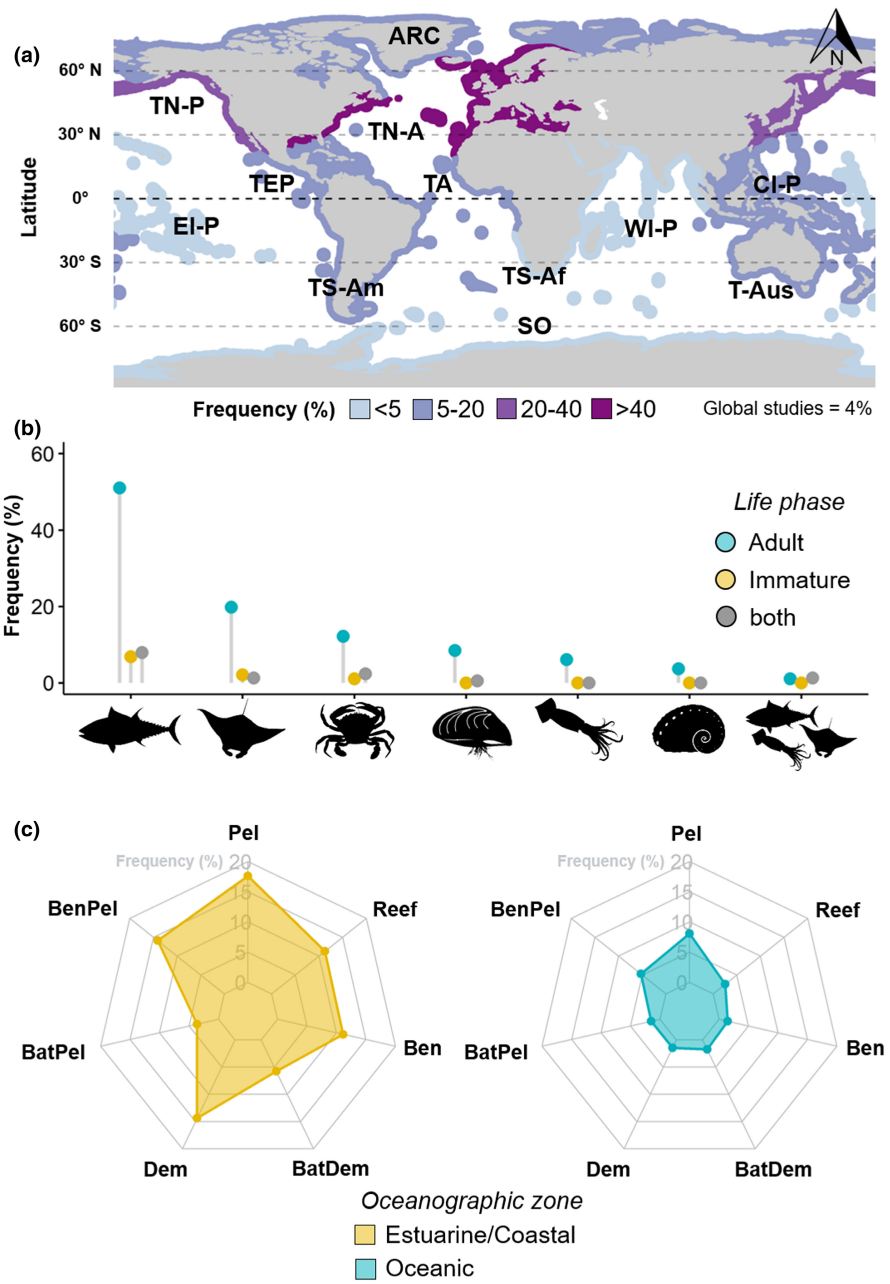

FIGURE 4 Frequency of studies on ENMs/SDMs in fishery resources among (a) marine biogeographic realm ARC: Arctic, TN-A: Temperate Northern Atlantic, TA: Tropical Atlantic, TS-Am: Temperate South America, TS-Af: Temperate Southern Africa, WI-P: Western Indo-Pacific, CI-P: Central Indo-Pacific, EI-P: Eastern Indo-Pacific, T-Aus: Temperate Australasia, TN-P: Temperate Northern Pacific, TEP: Tropical Eastern Pacific, SO: Southern Ocean; (b) taxonomic group (Actinopterygii, Elasmobranchii, Crustacea, Bivalvia, Cephalopoda, Gastropoda and combined commercial species) and life phase (adult, immature, both); (c) oceanographic zone (estuarine/coastal, oceanic) and behaviour (Pel: pelagic, BenPel: benthopelagic, BatPel: bathypelagic, Dem: demersal, BatDem: bathydemersal, Ben: benthic, Reef: reef-associated). Note that the frequency may be based in counts larger than the total amount of retained articles (378) due to the possibility of multiple fitting among categories. Credit of silhouette images to Becky Barnes, Hans Hillewaert, Nick Schooler, Stuart Humphries and Tauana Cunha downloaded from https://beta.phylopic.org/.

to the growing computational power that allows researchers to develop models with some mastery. Additionally, the expansion of free software, open languages (e.g., R, Python), forums, tutorials, and courses (Cobos et al., 2019; Peterson et al., 2022) is increasing users familiarity. Computational power also increases the number of possible answers given by scientists, who have been incorporating increasing complexity into the models (Coll et al., 2020). Moreover, three main collaborative groups can be observed, linked to historically major global fishery resource consumers (USA, Japan, and Europe; FAO, 2020) and well-explored oceanic basins (Pacific, Atlantic and Mediterranean). This can indicate a bias of personal interest of researchers or commercial interest of such countries: gathering the maximum available data together to improve predictability and sustainability of shared fishery stocks.

Applying ENMs/SDMs to estimate the current distribution of fishery resources is the default. This is expected since the knowledge of where and when to find fishery resources is the greatest purpose for fishers, managers and industry. For some privileged fishers, these models make it possible to easily find fish and invertebrates over the enormous area occupied by the oceans, beyond its standard use for research and management purposes. Additionally, understanding species distribution in space has interested ecologists for a long time (Elton, 1927; Grinnell, 1917; Hutchinson, 1957; Soberón & Peterson, 2005; Wallace, 1860). Second, the threat of climate change is a constant topic in current ENMs/SDMs publications. The Intergovernmental Panel on Climate Change (IPCC) has highlighted the consequences of ocean warming, acidification, and biodiversity loss, among other human-made impacts (IPCC, 2019). In the case of fishery resources, biomass reduction in some stocks

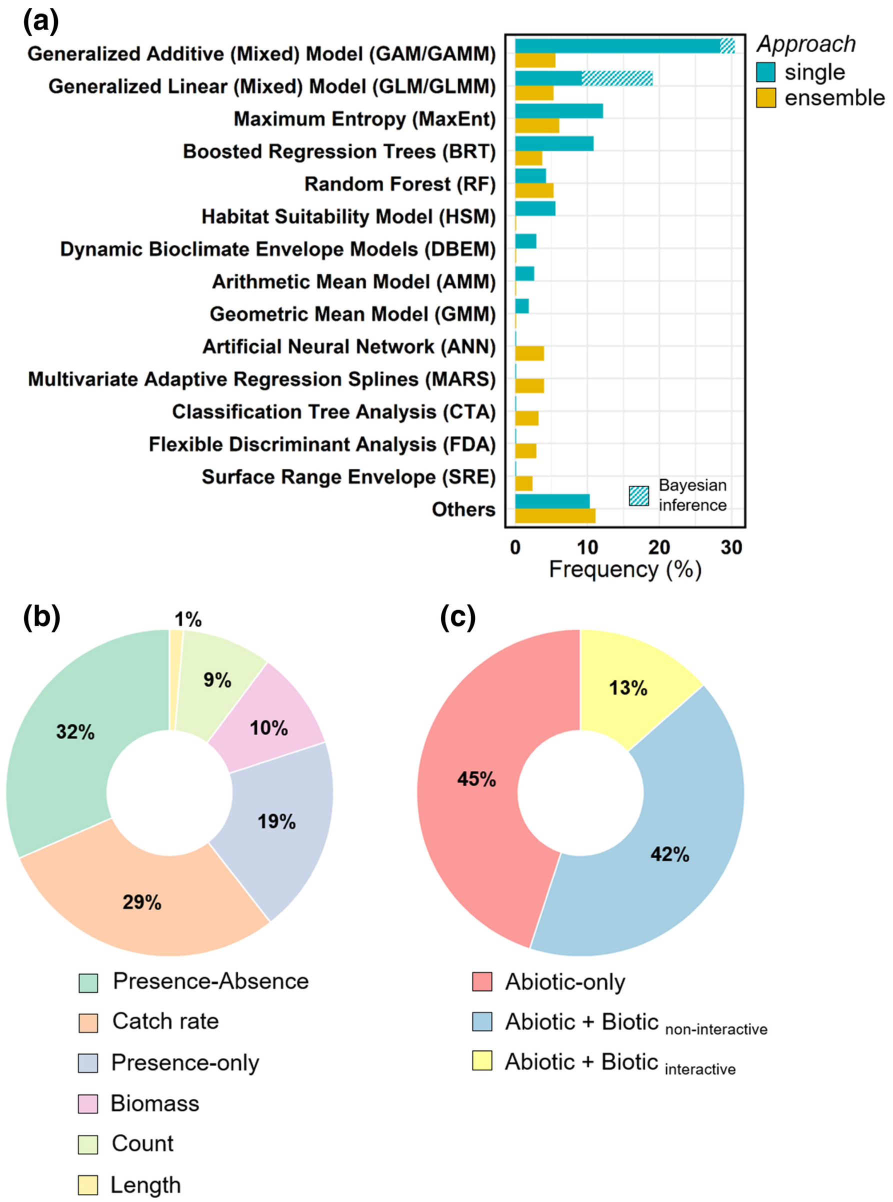

FIGURE 5 (a) Barplot of frequency of studies on ENMs/SDMs in fishery resources among applied methods. List of methods included in 'Others' is available in Appendix S2. Percentage of the used (b) biological and (c) environmental data publishing about ENMs/SDMs in fishery resources. Note that the frequency may be based in counts larger than the total amount of retained articles (378) due to the possibility of multiple fitting among categories.

and displacement of species (Cheung et al., 2009, 2010, 2013) have hazardous impacts for worldwide food security; valuing the development of predictive ENMs/SDMs. Third, scientists have considered the spatiotemporal dynamic variation of fishery stocks in assessments, improving the estimate of indices (Berger et al., 2017) and, consequently, of fishery management.

4.2 | Characteristics linked to fishery resources

There is a stark difference between northern and southern biogeographic realms considering the number of ENM/SDM articles. The obvious reasoning is the heavy economic investment in science made by the northern first world countries, which are interested in maintaining productive fisheries (Hilborn et al., 2020). To fulfil this goal, we speculate that these countries find in the spatiotemporal distribution modelling (through ENMs/SDMs) an opportunity to make their fisheries objective, profitable, and sustainable (e.g. Abecasis et al., 2014), but specific destination of financial analysis is necessary to elucidate this point. For example, the Temperate Northern Atlantic has concentrated studies on the North Sea, Mid-Atlantic Bight, northern Gulf of Mexico and Mediterranean Sea, which are surrounded and/or under the control of the USA, Canada, and European countries. Other countries, such as China and Japan, are historically dependent on seafood for their food security (Ghose, 2014), which explains the high usage of modelling in the Northern Temperate Pacific. The major groups among collaborations reinforce the idea of interest of countries to study their own sea areas (Figure 3). On the other hand, the Eastern Indo-Pacific, Temperate Southern Africa, Western-Indo Pacific, and Southern Ocean were the least studied realms, an alarming gap, considering that these regions are continuously explored, mainly by foreign industrial fleets (Hilborn et al., 2020). This pattern among biogeographic realms does not reflect the most important fishery hotspots well, highlighting the less studied coast off Peru and Chile, which yield the largest catches of anchovy (FAO, 2020).

Actinopterygii were by far the most studied taxonomic group, followed by Elasmobranchii and Crustacea. Bony and cartilaginous fishes are known to be the most captured resources in oceanographic basins, reaching approximately 72,000 thousand tonnes in 2020 (85% of total catch) (combined report as finfish, FAO, 2020). The modelled bony fish species include some of the most worldwide captured fishery resources such as anchoveta (*Engraulis ringens*, Engraulidae) (Silva et al., 2019), cod (*Gadus chalcogrammus*, Gadidae) and (*G. morhua*, Gadidae) (Li et al., 2018; O'Leary et al., 2020), skipjack tuna (*Katsuwomus pelamis*, Scombridae) (Mugo & Saitoh, 2020), blue whiting (*Micromesistius poutassou*, Gadidae) (Miesner & Payne, 2018), European pilchard (*Sardina pilchardus*, Clupeidae) (Gordó-Vilaseca et al., 2021), and Pacific chub mackerel (*Scomber japonicas*, Scombridae) (Torrejón-Magallanes et al., 2021). Cartilaginous fishes compose a diverse taxonomic group that includes important fishery resources, such as the largely explored blue shark (*Prionace glauca*, Carcharhinidae) (Cortés et al., 2010; Maxwell et al., 2019). Other studied species, despite being strongly appreciated for income and food, are considered vulnerable, endangered, or critically endangered by the IUCN Red List of Threatened Species (IUCN, 2022). Examples are the hammerheads (*Sphyrna lewini*, Sphyrnidae) and (*S. mokarran*, Sphyrnidae) (Chan et al., 2021), the whale shark (*Rhincodon typus*, Rhincodontidae) (Petatán-Ramírez et al., 2020), thorny skate (*Amblyraja radiate*, Rajidae) (Pennino et al., 2019), and spiny dogfish (*Squalus acanthias*, Squalidae) (Dell'Apa et al., 2017). Commercial crustaceans include crabs, swimming crabs, shrimp, krill, and lobsters (e.g., Clavel-Henry et al., 2020; Hovey et al., 2012; Luan et al., 2018; Naimullah et al., 2020; Silk et al., 2016), which are the third most captured group (FAO, 2020). Most modelled Crustacea species are likely coastal due to challenges of rare individuals and benthic environmental sampling (such as granulometry and rugosity) of benthic deep-sea crustaceans (Hovey et al., 2012). Bivalvia, Cephalopoda, and Gastropoda include diverse mussels, oysters, squids, octopuses, and abalones (e.g., Ángeles-González et al., 2021; Bergström et al., 2021; Gong et al., 2021; Russell et al., 2012; Stirling et al., 2016). Surprisingly, these three taxonomic groups appeared at almost the same frequency among articles. We expected the highlight of the cephalopods because they represent the highest catch among mollusks (such as Ommastrephidae species; e.g., Gong et al., 2014; Yu et al., 2019; Alabia et al., 2020) (FAO, 2020). More frequently modelled adult life phase instead of immature phases (egg, larval, and juvenile) can be explained by two possibilities: (1) the accessibility of data through fishery activity which is focused mainly on the larger and heavier adults, and (2) the majority of species strongly change their habitats and behaviours between immature and adult phases, which implies that spatiotemporal modelling of younger phases may not improve the predictability of the distribution of the profitable and fishery-desired adults.

Studies covering estuarine/coastal zones were more frequent than in oceanic zones. This trend appears to be related to the easy access and significant availability of data in estuarine/coastal zones (Robinson et al., 2011), in contrast to the more difficult access to aphotic, abyssal and hadal, ocean zones, which limit the number of studies available. For example, the relative proximity to the mainland and the easier and cheaper sampling facilitate access to data by researchers from the Patos Lagoon estuary and the adjacent marine coast (southern Brazil) and, consequently, allow long-term observations among many taxonomic groups (Lemos et al., 2022). On the other hand, access to deeper areas is scarce, hindering direct observations of both biotic and abiotic data, making it difficult to model the distribution of species, even for those based on presence alone. Additionally, estuarine and coastal zones are known to be some of the most productive in the oceans, resulting in a greater amount of fishery resources and fishing effort (Kapetsky & Lasserre, 1984; Alongi, 1998), and partially explaining the discrepancy between estuarine/coastal and oceanic zones. Moreover, ENMs/SDMs were more common in regard to behaviours such as demersal, benthic, and reef-associated at estuarine/coastal than oceanic zones. Demersal organisms swim and forage near the sea floor, benthic organisms live on or inside the sediment, and reef-associated organisms depend on consolidated substrate structured by corals for refuge, feeding and/or reproduction (Froese & Pauly, 2022). Such behaviours are related to benthic environments, which are, as mentioned before, more accessible in estuarine/coastal zones than in oceanic waters. In oceanic zones, the more frequent studies on pelagic and benthopelagic behaviours (organisms that live and feed totally or partially near the surface of open ocean, respectively) can be explained by the growing use of surface environmental layers available by remote sensing (He et al., 2015; Randin et al., 2020) coupled with catch data derived from oceanic fisheries (e.g., longline, purse seine).

4.3 | Characteristics linked to methods

Among the most applied methods five are noteworthy (from most to fewer): GAM, MaxEnt, GLM, BRT, and RF (list of abbreviations in Table 1). These methods can be classified in major groups as proposed by Martínez-Minaya et al. (2018). The first includes MaxEnt, which was developed to address presence-only datasets and describe some measure of habitat suitability (Phillips et al., 2006). The second includes BRT and RF, which involve machine-learning algorithms that are iterative, generally averaging multiple models among different subsets of the data (Franklin, 2010). The third includes GAM and GLM, both are statistical models, GAM being an expansion of GLM. GAM does not assume a specific form of relationship between the dependent variable and the covariates, contrary to GLM, which assumes a fixed linear or other parametric form (Guisan et al., 2002). We found applied GAM and GLM using fixed effects but also a mix between fixed and random effects (named GAMM and GLMM). This seems to be a strategy for authors to explicitly model the nonindependence in data (Harrison et al., 2018), such as the time-effect (month, year). The application of Bayesian framework has growing in recent years (Kinas & Andrade, 2021). Within this paradigm, we can combine (via Bayes' Theorem) data uncertainty (via likelihood function) with previous information about all parameters governing the different models (introduced via prior distributions), resulting in the posterior probability distribution, which contains all information necessary about the parameter (Kinas & Andrade, 2021; Korner-Nievergelt et al., 2015; Martínez-Minaya et al., 2018). The Integrated Nested Laplace Approximation (INLA) was the most used in Bayesian inference compared to others, such as Markov Chain Monte Carlo (MCMC). The precision and computational efficiency in many latent Gaussian models make the INLA largely applicable in fishery context (Martínez-Minaya et al., 2018; Rue et al., 2017). A previous bibliometric study found more frequent use of MaxEnt than GLM and GAM when considering all marine taxonomic groups (Melo-Merino et al., 2020), which was the opposite that we found. This finding can be explained by the major accessibility of higher quality input data (presence-absence, catch rate) for fishery resources than for species not targeted in fisheries. Frequently, these latter species have solely presence-only (geographic position) data available from large databases (e.g., GBIF, OBIS) – the sufficient input data for MaxEnt modelling. Furthermore, an ensemble approach was a recurring practice among articles, which is the combined application of multiple methods commonly averaging the resulting projections. Some authors argue that ensemble improves decision-making in face of the uncertainty (Araújo & New, 2007; Jones et al., 2012); however, it is debatable whether ensemble modelling is better than a single-algorithm approach.

Presence-only, presence-absence, and catch rate biological data were used in 80% of all articles. The first two types of data have been widely used for ENMs/SDMs because of their availability at a broader spatial scale (Elith et al., 2006; Elith & Leathwick, 2009). Large repositories such as the GBIF and OBIS contain many occurrence points of these types of biological data, favouring their use by scientists. Catch rates are largely analysed in fishery data since any catch (count, weight) is strongly related to a measure of effort (net length, number of hooks, and time fishing) (Schnute, 1985). It is noteworthy that presence-only, presence-absence, and catch rate are nested data. It means, for example, that catch rate also has information of presence-only and presence-absence.

In summary, all methods used abiotic variables and mostly used abiotic-only or abiotic plus noninteractive biotic variables. Abiotic variables are defined as "conditions, including aspects of climate, physical environment, edaphic conditions, etc, that impose physiological limits on species' ability to persist" (Soberón & Peterson, 2005). Variables such as sea surface temperature, depth, salinity, latitude, longitude, and granulometry were often considered in modelling. Their use can be explained by static values (e.g., depth, latitude) and/or by ease for sampling (e.g., temperature). The aforementioned definition is also valid for biotic variables if the presence of the modelled species does not interact in a short-term period with such variables – scenopoetic or noninteractive biotic variables (Soberón & Nakamura, 2009). This is the case for phytoplankton concentration (or similar, chlorophyll-a concentration and primary production) in which the interaction with secondary, tertiary, and top trophic levels generally has only bottom-up and not top-down effects (Frederiksen et al., 2006). The noninteractive biotic variables in our bibliometric analyses mainly included the phytoplankton concentration (or similar) and, to a lesser extent, seagrass concentration and reef presence. Biotic interactive variables (or bionomic variables, Soberón & Nakamura, 2009) appeared in only 13%. The use of this kind of variable is rare, but distribution estimates of species at broad scales may be more accurate if calibration of ENMs includes relevant biotic variables (Araújo et al., 2014; Barber et al., 2021; Gherghel et al., 2018; Stephenson et al., 2022). However, it is important to highlight that the inclusion of biotic variables in modelling must consider the complexity of the bidirectional effect of variables. For example, the predation risk sometimes varies with animal behaviour and environmental conditions (Suraci et al., 2022), which implies that the input of such biotic variables (e.g., prey abundance) may not correspond to the real effect on the modelled species. Some methodological strategies such as hierarchical structure on the regression coefficients (Wilkinson et al., 2019) and shared component analysis (Izquierdo et al., 2021; Paradinas et al., 2017, 2020; Wilkinson et al., 2019) have emerged as extensions of ENMs/SDMs to capture the effects of biotic interactions (also known as joint species distribution models; JSDMs), even though their capability to separate environmental effects from biotic interactions is still being discussed (Poggiato et al., 2021). In our survey, the following biotic interactive variables were noteworthy: presence/density of prey, presence/density of competitor, habitat species diversity, dominant biota and, co-occurrence of the same species in different life stages. Finally, we clarify that the classification of biotic variables in interactive or noninteractive was based on general assumptions for each variable. However, it is known that biological interactions are strongly influenced by spatial and temporal scales (Record et al., 2018). For example, in a high spatial resolution (smaller grid), the interaction between the phytoplankton concentration and a fishery resource (e.g. anchovy) can be locally bidirectional or, in other words, the abundance of anchovy can reduce the phytoplankton concentration. Only knowing the biological characteristics of organisms and the used scale would correctly classify biotic variables.

4.4 | Gaps and suggestions

Studies of ENM/SDMs on fisheries resources among southern marine biographic realms are a gap in this research topic, resulting in a loss of opportunity. In the face of data poor fisheries statistics, the use of correlative spatial modelling approach should be a priority to understand spatiotemporal patterns of explored species due to its capability to 'extrapolate' (considering limitations) the scarce samples in hand. In addition to self-investment in spatial modelling approaches, we suggest that first-world countries would help the emergent and poor countries through scientific collaborations. After reducing the discrepancy between studied marine realms, southern hemisphere countries would be able to better understand spatiotemporal trends of explored species and then propose management alternatives for national and shared stocks. Studies on immature life phases, Mollusca taxonomic group, benthic-associated behaviours in oceanic zones, and focusing on species invasion or past climates also are gaps. Aspects of the distribution of an entire life cycle and under other climatic conditions can be of great value to understand biogeographic features and fisheries catches. Some species of Mollusca (e.g., Humboldt squid, *Dosicus gigas*) and benthic-associated behaviours in oceanic zones (e.g., *Chaceon* spp.) contribute significantly to fisheries catch worldwide and should not be neglected.

Finally, more is not better: we recommend that in addition to a more frequent use of ENM/SDMs, a higher quality is needed for the biological input data (preferably catch rate) and for the applied methods (those capable to also consider biological beyond the abiotic component).

5 | CONCLUSIONS

This is the first bibliometric study seeking to determine the state of the art on the interface between ENMs/SDMs and fishery resources. Additionally, compiling 378 of 930 accessed articles and classifying fishery resources and methods represents a considerable effort to generate up-to-date information about this issue. A clear tendency of an increasing number of articles demonstrates the interest of researchers, journals, and collaborative countries (centred in three major groups) in improving their knowledge and maintaining profitable and sustainable fisheries. More studies in the Temperate Northern Atlantic and Temperate Northern Pacific marine biographic realms seem to be related to first world countries' interest in exploring shared fishery stocks. Additionally, more studies are directly related to more captured and consumed taxonomic groups: bony and cartilaginous fish. Benthic-associated behaviours (such as demersal and benthic) are more frequent in estuarine/coastal oceanographic zones than in oceanic zones (where pelagic and benthopelagic behaviours predominate), probably due to the major accessibility provided by proximity to land. Fourteen methods have been well applied, mainly the most popular frequentist GAM, GLM, and MaxEnt; however, other alternatives, such as ensemble approach and Bayesian inference, have been increasingly explored considering their quality-of-fit and forecasting. Large repositories and fisheries data support the availability of presence-absence, presence-only, and catch rate data for researchers, explaining their popular use. Furthermore, abiotic and noninteractive biotic variables are largely used due for their static values and/or ease of measurement, however, although rare, interactive biotic variables may improve the current distribution modelling of fishery resources. Last, studies among southern marine biographic realms, immature life phases, Mollusca taxonomic groups, benthic-associated behaviours in oceanic zones, and focusing on species invasion or past climates are gaps in this research topic, and must receive more attention in the future. We hope the list of articles available in Appendix S1 and S2, and the results presented here provide a baseline for the current status (strengths, limits and gaps) of the interface between the ENMs/SDMs and fishery resources.

AUTHOR CONTRIBUTIONS

LdSR: Conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, visualization, writing original draft, writing – review and editing; MGP: supervision, validation, writing – review and editing; DC: supervision, validation, writing – review and editing; EK: data curation, methodology, formal analysis, investigation, methodology, writing – review and editing; PGK: supervision, validation, writing – review and editing; FGB: conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, writing – review and editing; LGC: conceptualization, supervision, validation, writing – review and editing.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The list of articles is available in Appendix S1 and S2.

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SUPPORTING INFORMATION

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