

Species' traits and exposure as a future lens for quantifying seabird bycatch vulnerability in global fisheries

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Keywords: bycatch, longline, purse seine, IUCN red list, seabird, trait, trawl, threatened species, vulnerability, vulnerability framework

Abstract

Fisheries bycatch, the incidental mortality of non-target species, is a global threat to seabirds and a major driver of their declines worldwide. Identifying the most vulnerable species is core to developing sustainable fisheries management strategies that aim to improve conservation outcomes. To advance this goal, we present a preliminary vulnerability framework that integrates dimensions of species' exposure, sensitivity, and adaptive capacity to fisheries bycatch to classify species into five vulnerability classes. The framework combines species' traits and distribution ranges for 341 seabirds, along with a spatially resolved fishing effort dataset. Overall, we find most species have high vulnerability scores for the sensitivity and adaptive capacity dimensions. By contrast, exposure is more variable across species, and thus the median scores calculated within seabird families is low. We further find 46 species have high exposure to fishing activities, but are not identified as vulnerable to bycatch, whilst 133 species have lower exposure, but are vulnerable to bycatch. Thus, the framework has been valuable for revealing patterns between and within the vulnerability dimensions. Still, further methodological development, additional traits, and greater availability of threat data are required to advance the framework and provide a new lens for quantifying seabird bycatch vulnerability that complements existing efforts, such as the International Union for Conservation of Nature (IUCN) Red List.

1 **Introduction**

2 As of 2018, the global fishing fleet is estimated at 4.56 million fishing vessels of various sizes
3 (FAO 2020). Fisheries bycatch, the incidental mortality of non-target species, is a serious threat
4 to seabirds, driving seabird population declines worldwide (Dias et al. 2019). Thus, key goals for
5 successful fisheries management and conservation are to identify vulnerable non-target species
6 and develop bycatch mitigation strategies. Yet, these goals pose global challenges because
7 seabirds are wide ranging and encounter fishing activities in various national and international
8 waters at different stages of their life history (Komoroske and Lewison 2015). Better
9 understanding of the factors affecting vulnerability of species to bycatch is an essential step
10 towards predicting which species are most at risk and working to mitigate bycatch threats.

11
12 While seabird bycatch is widespread, a global quantification of seabird vulnerability to fisheries
13 bycatch in multiple gear types (e.g. longline, trawl and purse seine) is lacking because bycatch
14 data are scarce (Anderson et al. 2011, Hedd et al. 2016, Suazo et al. 2017, Zhou et al. 2019).
15 There is very low observer coverage aboard fishing vessels, and existing data has poor species
16 discrimination and only coarse quantification (Bartle 1991, Weimerskirch et al. 2000, Sullivan et
17 al. 2006, Anderson et al. 2011, Hedd et al. 2016, Suazo et al. 2017). Thus, bycatch mortality of
18 high-risk species may be undetected by on board vessels by fishers and observers, and therefore
19 under- or unreported to databases that collate species' threat data such as the International Union
20 for Conservation of Nature (IUCN) Red List (iucnredlist.org). Coupling traits with fisheries
21 exposure information could offer a complementary lens to existing methods and provide insights
22 into different dimensions of seabird bycatch vulnerability.

23
24 Trait-based approaches have emerged as being important for advancing conservation efforts
25 (Miatta et al. 2021), where traits represent fundamental biological attributes of organisms
26 measured at the individual level (Violle et al. 2007, Gallagher et al. 2020). Furthermore,
27 selecting ecologically meaningful and interpretable traits can relate to species' vulnerabilities to
28 threats (Zhou et al. 2019, Richards et al. 2021). As an exceptionally well-studied group, detailed
29 information is available on the life history, behavioural and ecological traits of seabirds for
30 predictive trait-based analyses (Tavares et al. 2019, Richards et al. 2021). Thus, integrating

31 freely available global threat datasets with species traits in a vulnerability framework may be a
32 valuable tool to identify the seabird species most vulnerable to gear-specific bycatch.

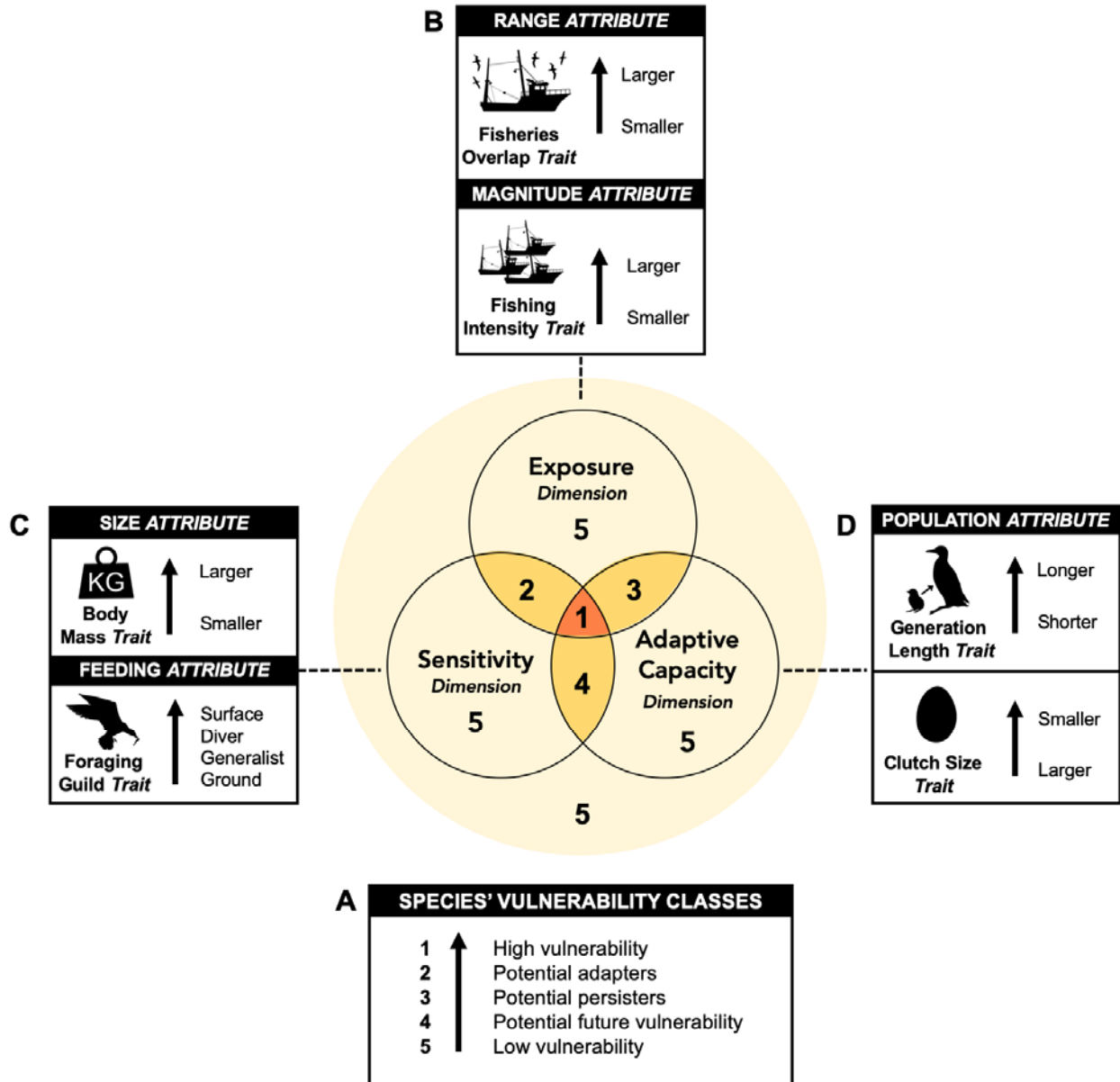
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34 A species' vulnerability to bycatch is determined by both extrinsic (threats) and intrinsic (traits)
35 factors. Specifically, such factors include the interplay between a species' exposure, sensitivity,
36 and capacity to adapt in response to bycatch (Foden et al. 2013, Potter et al. 2017, Butt and
37 Gallagher 2018). Firstly, exposure encompasses the extent to which species' ranges overlap with
38 fishing activities and the magnitude of activities experienced. For example, wide-ranging pelagic
39 foragers, such as albatrosses, overlap with a variety of fishing gears and fleets throughout their
40 lives (Clay et al. 2019). Secondly, sensitivity traits represent a species' likelihood of bycatch
41 mortality when it interacts with fisheries. For example, large seabirds have a greater risk of
42 bycatch mortality than smaller seabirds (Zhou et al. 2019). Finally, adaptive capacity traits
43 describe the ability for populations to adapt and recover from bycatch mortalities. For example,
44 bycatch will have a greater impact on seabirds with slow reproductive rates, such as albatross
45 and auks, which lay a single egg per season and reach sexual maturity after five to ten years.

46
47 Coupling a dataset of traits with seabird global range maps and a spatially resolved gear-specific
48 fishing dataset could provide a new lens for quantifying seabird bycatch vulnerability that would
49 complement existing efforts, such as the IUCN Red List. Here we (1) develop a framework for
50 quantifying seabird bycatch vulnerability to multiple gear types; (2) analyse the emerging
51 patterns of seabird bycatch vulnerability based on available data and traits; and (3) discuss future
52 directions and visions for the vulnerability framework.

53 **Building a vulnerability framework**

54 Here we modify a framework that has previously been applied to a diversity of species from
55 birds and trees to amphibians and corals (Foden et al. 2013, Potter et al. 2017), with the goal to
56 identify the seabird species most vulnerable to gear-specific bycatch (Fig. 1). Our intention is for
57 the vulnerability framework to be built upon and improved as more trait and threat data become
58 available in the future.

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Figure 1 | Framework to quantify species' vulnerability to bycatch. The combination of three dimensions: exposure, sensitivity and adaptive capacity, characterise five distinct species' vulnerability classes (Box A). Six traits associated with five overarching vulnerability attributes (Boxes B-D: Size, Feeding, Range, Magnitude, and Population) are used to quantify each vulnerability class. Black arrows indicate the direction of increased vulnerability. Modified from Foden et al. (2013) and Potter, Crane & Hargrove (2017).

70 The trait-based framework integrates three dimensions of bycatch vulnerability based on
71 exposure, sensitivity, and adaptive capacity. Each dimension encompasses a set of vulnerability
72 attributes (Size, Feeding, Range, Magnitude, Population) that in turn are represented by species'
73 traits (Fig. 1). The framework can be used to classify species into five vulnerability classes: high
74 vulnerability, potential adapters, potential persisters, potential future vulnerability, and low
75 vulnerability. Each has implications for conservation prioritisation and strategic planning (Foden
76 et al. 2013).

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78 **Assessing sensitivity and adaptive capacity to bycatch**

79 We selected body mass and foraging guild to infer the framework's sensitivity dimension (Fig.
80 1C), and used generation length and clutch size to quantify the adaptive capacity dimension (Fig.
81 1D). All traits were extracted from a recently compiled dataset of seabird traits (Richards et al.
82 2021).

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84 **Assessing exposure to bycatch**

85 To estimate the framework's exposure dimension, we quantified (1) overlap with fisheries
86 activities as the percentage of 1° global grid cells shared between species' ranges and each gear-
87 specific fishing activity, and (2) fishing intensity as the sum of all fishing hours in the
88 overlapping grid cells (Fig. 1B). To achieve this, we first extracted distribution polygons for 341
89 seabirds (BirdLife International, 2017) which represent the coarse distributions that species
90 likely occupy, and are presently the best available data for the seabird global ranges. We created
91 a 1° resolution global presence-absence matrix based on the seabird distribution polygons using
92 the package 'letsR' and function lets.presab (Vilela and Villalobos 2015). Second, we
93 downloaded the daily fishing effort data for longlines, trawls, and purse seines from Global
94 Fishing Watch, which classifies vessel activity based on vessel type and movements (Kroodsma
95 et al. 2018). For each gear type, fishing effort was summed per 1° global grid cell between 2015
96 and 2018. Finally, to ensure consistency between the species' distribution and gear-specific
97 fishing activity layers, we re-projected all spatial data to a raster format with the same coordinate
98 reference system (WGS84), resolution (1° x 1° global grid cells) and extent ($\pm 180^\circ$, $\pm 90^\circ$). To
99 achieve this, we used the package 'raster' and function rasterize (Hijmans 2020).

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101 **Trait Scoring and Weighting**

102 Each trait, attribute and dimension were scored between 0 and 1, with 1 indicating the greatest
103 vulnerability to bycatch (Potter et al. 2017). This was achieved through a stepwise process. First,
104 all continuous traits from the vulnerability dimensions (body mass, clutch size, generation
105 length, overlap with fisheries, and fishing intensity) were broken into categories using the
106 Sturges algorithm which bins the traits based on their sample size and distribution of values
107 (Sturges 1926). All trait categories were then scored from high to low with ordinal variables
108 based on increased vulnerability to bycatch (Appendix 1-3). To ensure the prioritisation analysis
109 predictably weights the criteria (Mace et al. 2007), all scores were scaled between zero and one
110 and weighted by the frequency of trait occurrence (Potter et al. 2017).

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112 The following worked example represents the scoring and weighting steps for a trait with four
113 categories:

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115 Trait category 1 (lowest vulnerability) = 0

116 Trait category 2 = $(n_1 + n_2)/n_{\text{total}}$

117 Trait category 3 = $(n_1 + n_2 + n_3)/n_{\text{total}}$

118 Trait category 4 (highest vulnerability) = $(n_1 + n_2 + n_3 + n_4)/n_{\text{total}} = 1$

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120 Where n is the number of species per trait category and n_{total} is the total number of species.

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122 For example, foraging guild contains four categories: ground forager (category 1 = 13 species),
123 generalist forager (category 2 = 63 species), diving forager (category 3 = 121 species) and
124 surface forager (category 4 = 144 species), and n_{total} for this study is 341 species. Ground forager
125 has the lowest conservation priority therefore is given a score of 0. All other foraging strategies
126 are weighted proportionally based on the number of species within that category and the lower
127 categories (Potter et al. 2017). Therefore, generalist forager's score is $(13 + 63) / 341 = 0.22$,
128 diving forager's score is $(13 + 63 + 121) / 341 = 0.58$ and surface foragers, with the greatest

129 conservation priority, have a score of $(13 + 63 + 121 + 144) / 341 = 1$. These equations are applied
130 to each trait independently, and the number of trait categories varies between 3 to 5 per trait.

131

132 **Vulnerability Classes**

133 We categorise species into vulnerability classes (Fig. 1A) based on a dimension score threshold
134 of 55%. This threshold was decided from a sensitivity test by balancing between excluding all
135 vulnerable species because thresholds were too high, and ensuring minimal species changes
136 between threshold levels across all gear types (Fig. A4.1). If all dimensions (exposure,
137 sensitivity, and adaptive capacity) have a score greater or equal to 55%, species are highly
138 vulnerable to bycatch, therefore, were classified into the “high vulnerability” class. If the scores
139 of sensitivity and exposure were greater or equal to 55%, but adaptive capacity was less than
140 55%, species were considered to have high vulnerability with potential adaptive capacity, and
141 were assigned to the “potential adapters” class. If the scores of adaptive capacity and exposure
142 were greater or equal to 55%, but sensitivity was less than 55%, species were considered to have
143 high vulnerability with potential to persist and were assigned to the “potential persisters” class.
144 Species were classified into the “potential future vulnerability” class if the scores of adaptive
145 capacity and sensitivity were greater or equal to 55%, but exposure was less than 55%. If all
146 dimensions have a score less than 55%, or if only one dimension has a score greater or equal to
147 55%, species had low overall vulnerability and were assigned to the “low vulnerability” class.
148 This approach was repeated for the three gear types (longline, trawl and purse seine). Thus, all
149 species received vulnerability scores and classes associated with each gear type.

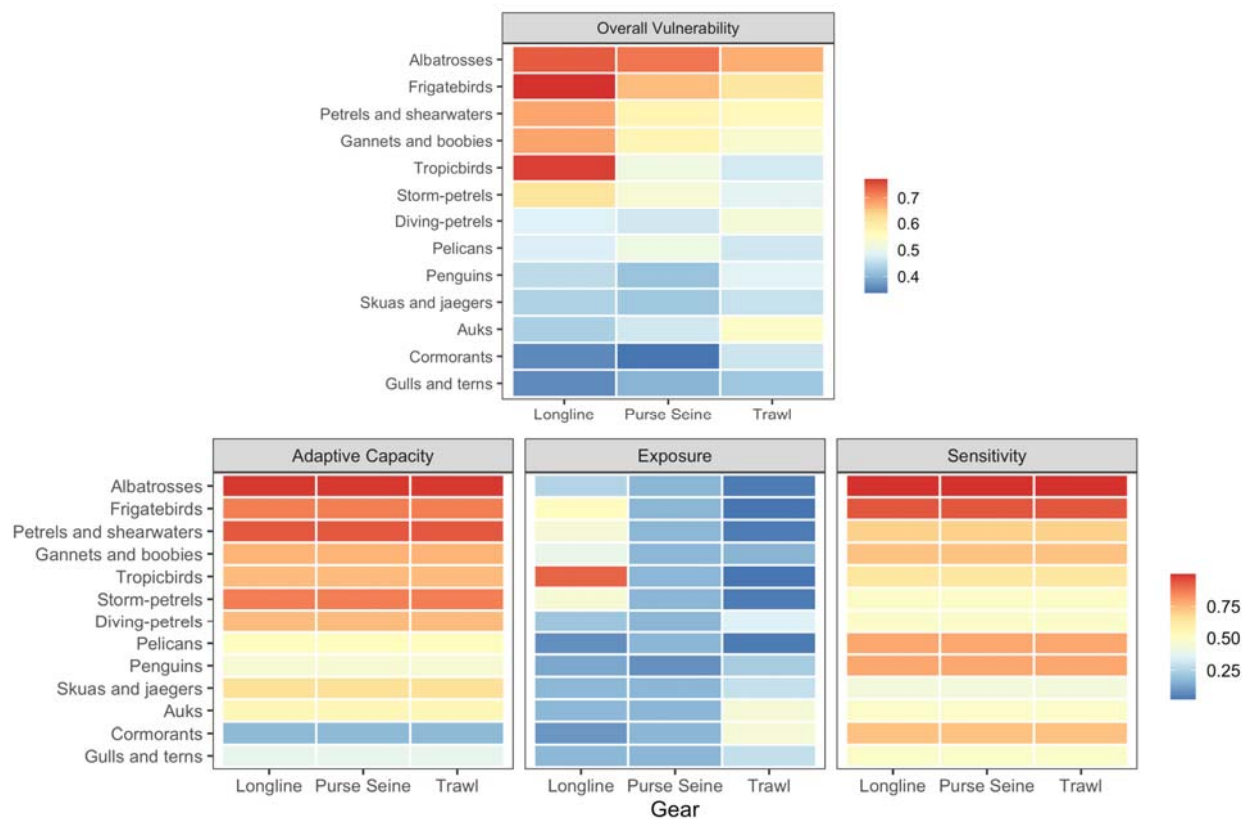
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151 All analyses were performed in R version 4.0.2 (R Core Team 2020).

152 **Emerging patterns of species’ vulnerability to bycatch**

153 Our preliminary vulnerability framework revealed emerging patterns within the vulnerability
154 dimensions and classes, with species’ vulnerability varying across the three gear types and
155 dimensions (Fig. 2 & 3; Appendix 5). Albatrosses have the highest overall vulnerability followed
156 by frigatebirds, petrels, and shearwaters, while gulls, terns, and cormorants have the lowest

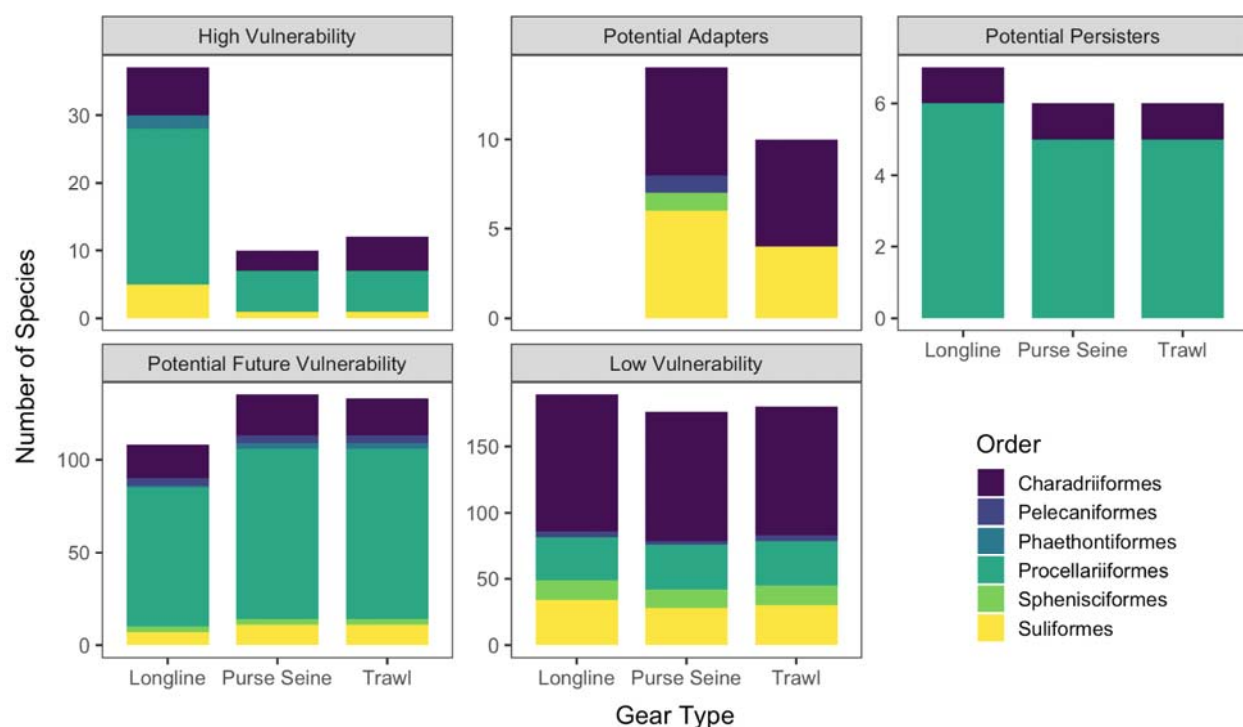
157 overall vulnerability (Fig. 2). All seabird families have relatively high sensitivity (median = 0.70)
158 and little capacity to adapt (median = 0.74) in response to bycatch (Fig. 2). By contrast, exposure
159 is more variable and has emerged as an important vulnerability dimension. While the median
160 exposure across families is low (median = 0.17; Fig. 2), a number of families and individual
161 species have high exposure scores. For example, the Wedge-tailed Shearwater
162 (*Ardenna pacifica*) has a longline exposure score of 0.95, the Northern Fulmar (*Fulmarus*
163 *glacialis*) has a trawl exposure score of 0.90, and the Black-tailed gull (*Larus crassirostris*) has a
164 purse seine exposure score of 0.97.
165



166
167 **Figure 2 |** Median overall vulnerability, adaptive capacity, exposure, and sensitivity scores
168 of all seabird families to longline, purse seine, and trawl gear types.

169
170 Furthermore, we find 46 species have high exposure (score $\geq 75\%$) to at least one gear type, but
171 are not identified as vulnerable to bycatch by the IUCN threat classification scheme (threats 5.4.3
172 & 5.4.4 from <https://www.iucnredlist.org/resources/threat-classification-scheme>). These species
173 were predominantly gulls and terns ($n = 16$), petrels and shearwaters ($n = 13$), and storm-petrels

174 (n = 7). A total of 133 species have lower exposure (score < 75%) to at least one gear type, but
 175 are identified as vulnerable to bycatch by the IUCN. These species were predominantly petrels
 176 and shearwaters (n = 31), albatrosses (n = 22), auks (n = 19), and gulls and terns (n = 19).
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180 **Figure 3 |** The number of species falling into each vulnerability class for longline, purse
 181 seine and trawl gear types. Charadriiformes encompass gulls, tern, skuas, auks, jaegers;
 182 Pelecaniformes are pelicans; Phaethontiformes are tropicbirds; Procellariiformes encompass
 183 albatross, petrels, shearwaters; Sphenisciformes are penguins; Suliformes encompass gannets,
 184 boobies, cormorants, frigatebirds.

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187 We further find taxonomic differences between the five vulnerability classes. Specifically,
 188 species falling into the high vulnerability class (highest scores across all three dimensions) were
 189 predominantly albatrosses, petrels, and shearwaters (Fig. 3; Appendix 5). The most frequent
 190 species within the potential adapters class (high sensitivity and exposure scores, but do have
 191 adaptive capacity due to low scores) were gulls and cormorants (Fig. 3; Appendix 5). Potential
 192 persisters (low sensitivity score, high adaptive capacity and exposure scores) were typically

193 storm-petrels and shearwaters (Fig. 3; Appendix 5). The potential future vulnerability class (high
194 scores for sensitivity and adaptive capacity, low score for exposure) was commonly composed of
195 albatrosses, petrels, and shearwaters (Fig. 3; Appendix 5). Finally, species classified with low
196 vulnerability (low scores across all dimensions, or a high score for only one dimension) were
197 predominantly gulls and terns (Fig. 3; Appendix 5).

198 **Vulnerability framework limitations**

199 The vulnerability framework identified 62% (n = 32) more species that may be vulnerable to
200 bycatch (those falling into the high vulnerability class), but are not currently recognised by the
201 IUCN threat classification scheme as threatened from bycatch. Furthermore, it is important to
202 note that in its present form, the framework miss-classified 36% (n = 70) of the species identified
203 as threatened from bycatch by the IUCN into the low vulnerability class and 44% (n = 64) into
204 the potential future vulnerability class. These differences are likely attributed to limitations in
205 trait selection within the vulnerability framework's dimensions. For example, we do not include
206 a species' boldness or propensity to interact with vessels because these traits are not available for
207 all seabirds. To increase the framework's value, we encourage its further development in the
208 future with suggestions listed below.

209 **Future directions for the vulnerability framework**

210 While the framework has been valuable for revealing patterns between and within the
211 vulnerability dimensions, data limitations are presently impeding its full functioning to
212 effectively classify species into their vulnerability classes. However, we believe the framework
213 could become a valuable tool in the future as additional and finer-scale traits and threat data
214 become available because the framework is highly adaptable to spatial and temporal variations in
215 traits and threats. To aid in its replication and development in future analyses, we provide the R
216 code used to build the framework.

217

218 **Trait and dimension improvements**

219 While an array of traits are available for seabirds, to strengthen the vulnerability framework's
220 dimensions, additional efforts are required to compile traits that are not currently available for all

221 seabirds. For example, to improve the sensitivity dimension, future studies may include traits that
222 capture a species' likelihood of interacting with fishing vessels e.g., boldness, opportunism,
223 competitive ability, and whether they follow ships or not (e.g., Orben et al. 2021). To advance
224 the adaptive capacity dimension, adding additional metrics that relate to breeding and population
225 responses may be important, such as breeding frequency, productivity, and adult survival.
226 Finally, taking advantage of extensive seabird biologging data (e.g. seabirdtracking.org) will be
227 imperative to refine the spatiotemporal resolution of the exposure dimension, through shifting
228 the current fishing overlap metric to a quantification of fishing interaction rate. Moreover, adding
229 information on species abundance distributions and clustering behaviour may further improve
230 the exposure dimension.

231
232 **Fishing activity data improvements**
233 Fishing activity and seabird distributions vary daily, seasonally and annually. We therefore
234 acknowledge the limitation of using four years of aggregated fishing activity data. Future
235 modifications of the vulnerability framework may consider integrating the dynamic changes in
236 fishing activity. Moreover, including more gear types could further refine the approach. For
237 example, gillnets fisheries cause an estimated 400,000 seabird mortalities annually (Žydelis et al.
238 2013). However, we excluded this gear type from our analyses because it presently has poor
239 coverage within the Global Fishing Watch dataset. Finally, distributions of small-scale
240 subsistence, and illegal, unreported, and unregulated (IUU) fishing activities were unavailable,
241 and therefore not included in our vulnerability framework. Incorporating IUU fishing activities
242 in future studies could reveal species with unidentified vulnerability to bycatch.

243 **A future lens for conservation**

244 Few management actions have incorporated trait-based analyses into conservation strategies
245 (Miatta et al. 2021). However, we suggest that coupling species' traits with fisheries exposure
246 data within a vulnerability framework could offer an additional lens to advance ongoing
247 conservation measures and policy, such as the IUCN Red List. For example, there is very low
248 observer coverage aboard fishing vessels, and existing data has poor species discrimination and
249 only coarse quantification (Bartle 1991, Weimerskirch et al. 2000, Sullivan et al. 2006, Anderson
250 et al. 2011, Hedd et al. 2016, Suazo et al. 2017). Thus, bycatch mortality of high-risk species

251 may be undetected by on board vessels by fishers and observers, and therefore unreported to the
252 IUCN. The framework could complement vessel-based observations through identifying
253 vulnerable species for which little is known e.g., revealing high vulnerability of gadfly petrels
254 (*Pterodroma* sp.) to longline fleets.

255

256 **Local management**

257 This framework could further be extended to inform local management actions. For example, the
258 framework can be easily updated based on interannual and seasonal variation in fishing activity,
259 additional gear types, and reapplied at local scales. We therefore highly recommend future
260 studies couple extensive seabird tracking data with colony-specific trait information and regional
261 fisheries patterns to provide a powerful and informative tool for local management.

262 **Conclusions**

263 We combined fine-scale fisheries data with seabird traits and distribution data to build a
264 preliminary vulnerability framework that has the potential to identify species at risk from
265 bycatch and help set conservation priorities. Overall, we find most species have high
266 vulnerability scores for the sensitivity and adaptive capacity dimensions. Yet, the framework
267 revealed that species' exposure to fisheries was highly variable, suggesting that vulnerability to
268 bycatch may be dynamic and rapidly change with future developments in fishing. The
269 framework is highly flexible to trait changes within each vulnerability dimensions, therefore we
270 recommend that future studies compile the additional traits that are required before the
271 framework can be used as a tool to classify species into the five vulnerability classes. Thus,
272 coupling species' traits with fisheries exposure data within a vulnerability framework could be
273 used as an additional lens to aid ongoing conservation measures and policy. For example,
274 through supporting the efforts of the IUCN Red List and threat identification by suggesting
275 which species need to be especially well investigated and protected.

276 **Data Sharing and Accessibility**

277 Seabird traits were extracted from (Richards et al. 2021), specifically
278 <https://doi.org/10.5061/dryad.x69p8czhd>. Species distribution polygons are available upon

279 request from <http://datazone.birdlife.org/species/requestdis>. Fishing effort data for 2015 and
280 2016 are available for download, and data for 2017 and 2018 are available upon request from
281 <https://globalfishingwatch.org/>. Please contact Cerren Richards (cerrenrichards@gmail.com) for
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