Matters arising

Caution over the use of ecological big data for conservation

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ARISING FROM N. Queiroz et al. *Nature* https://doi.org/10.1038/s41586-019-1444-4 (2019)

Highly collaborative and data-intensive ecology studies are at the forefront of innovative solutions to global issues in conservation and natural resource management[1,2]. In their spatial risk assessment of industrialized fishing, Queiroz et al.[3] use big data and collaborative science to outline a global conservation blueprint for pelagic sharks. In Australian waters, their analysis incorrectly identified global risk 'hotspots' in areas that are not subject to fishing and where spatial closures and other management measures are already in place to protect sharks. We highlight the potential for large-scale global analyses to misdirect conservation efforts if not aligned with regional needs and priorities.

Although ecologists have enthusiastically adopted collaborative, data-driven approaches in recent years, limited attention has been given to the challenges in this emergent field, including the potential for these often highly impactful studies to confound management and conservation actions[4]. We applaud the collaborative effort by Queiroz et al.[3] in assimilating satellite tagging data on 1,800 large pelagic and neritic sharks generated by 153 authors. However, we also caution against the use of data-intensive methods for guiding policy at the global scale without proper acknowledgement of their risks, complexities and limitations.

In their paper, Queiroz et al.[3] identify Australia's North West Shelf (NWS) as a global fishing exposure hotspot for sharks on the basis of spatial overlap with purported drifting longline and purse seine fishing vessel movements, despite no such fishing having occurred during the past two decades in this area. When we downscaled the approach of Queiroz et al.[3], we found errors in the data used to evaluate fishing exposure in these waters that were derived using a machine learning approach applied to vessel automatic identification system (AIS) location data[5].

In Western Australian state waters—an area larger than the Bering Sea—99.8% of longline and 100% of purse seine AIS data were incorrectly classified by the machine learning algorithm (Table 1 and Fig. 1). Incorrect classifications included movement data from other types of commercial fishing vessels as well as non-fishing vessels. For example, 95% of the data for purse seines in Western Australia waters were attributed to the movements of the research vessel of our agency (which, incidentally, does not undertake purse seine or drifting longline surveys).

The area of the NWS identified as highest risk falls within a spatial closure of 0.8 million km^2 in which directed shark fishing has been prohibited since 2005[6]. Although an area to the northeast remains open to shark fishing, none has occurred since 2009[6] and a network of State and Commonwealth marine reserves has since been implemented over much of that area. Fishery-independent surveys carried out over a 17-year period confirm stable or increasing relative abundance and size of large sharks in the region[6]. Historically, the waters adjacent to the NWS shelf were indeed important fishing grounds for foreign drifting longline vessels before their exclusion from Australian waters in 1997[7], and for Australian vessels in the subsequent years[8]. Contemporary longlining by a domestic tuna and billfish fishery still occurs, although these vessels were absent from the AIS data used by Queiroz et al.[3]. Since 2005, the intensity of this fishery has decreased and its footprint shifted to the southwest[9].

The approach of Queiroz et al.[3] fared better at the scale of the entire Australian Exclusive Economic Zone and offshore territories (10.2 million km^2), where the tuna and billfish longline fleet operating off eastern Australia was correctly classified (Fig. 1). However, 51% of drifting longline data were still incorrect (Table 1) and, notably, several demersal trawlers were also misclassified as being part of the longline fleet. Data from these vessels led to the incorrect identification of another pelagic longline risk hotspot within the Great Barrier Reef Marine Park (Fig. 1), where this fishing method is not permitted. In the case of both the NWS and Great Barrier Reef, the fishing exposure hotspots identified were due to fewer than five vessels being misclassified, highlighting a presumably unexpected level of sensitivity in the analysis.

As illustrated here, although patterns identified in global analyses may be broadly informative, they can also be incorrect or misinformative at regional levels where there is the scope for misallocating resources for conservation and management. Framed alternatively,

Table 1 | Summary of machine-learning classified fishing effort data

	Western Australia		Australia and offshore territories	
Total area (million km^2)	2.27		10.2	
Gear type	Longline	Purse seine	Longline	Purse seine
Total classified vessels	11	3	76	15
Incorrectly classified vessels	9	3	24	11
Fishing hours	41,074	2,650	190,355	7,511
Incorrect fishing hours (%)	99.82%	100%	51%	82%

The machine-learning classified fishing effort data used by Queiroz et al.[3] to evaluate the risks to sharks from fishing in Western Australian and Australian maritime jurisdictions. The table shows the total number of vessels classified as using longlines or purse seine, and their respective fishing hours, along with the number of vessels and percentage of fishing hours found to be incorrect. Australia and offshore territories includes all offshore and sub-Antarctic territories and the Australian Antarctic Territory.

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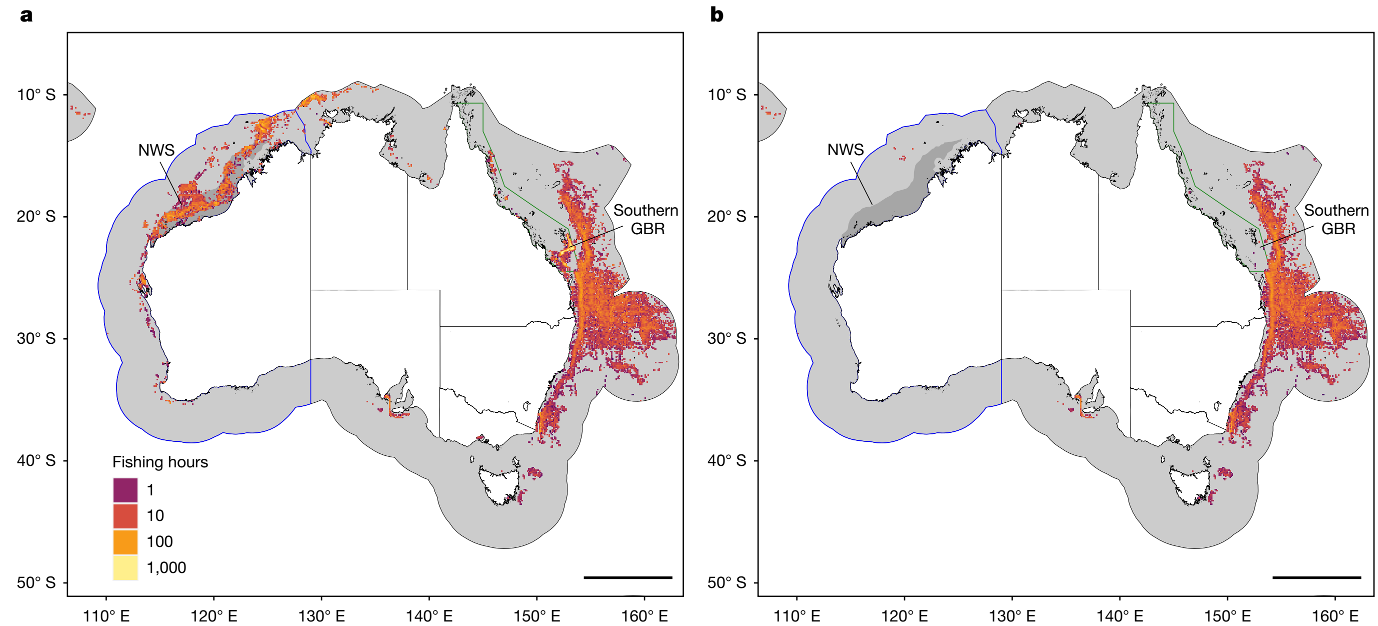

Fig. 1 | Machine-learning-classified fishing effort data (0.1° × 0.1° grid cells) used to evaluate the risk to sharks from pelagic longline and purse seine fishing in waters under Australian jurisdiction. a, Data used in the original analysis by Queiroz et al.[3]. **b**, Data that were correctly attributed to longline and purse seine fishing vessels. The NWS and the southern Great Barrier Reef (GBR) were identified as globally important 'hotspots' based on the spatial overlap of longline fishing and shark density. Grey shading shows the waters under Australian jurisdiction. The green line denotes the boundary of the Great Barrier Reef Marine Park. The blue line denotes the Western Australian maritime jurisdiction. Dark grey shading within Western Australian waters denotes the NWS. This figure was created with the statistical software R v.4.0.2[15]. Scale bars, 800 km.

what constitutes an acceptable level of accuracy at the global level may be unacceptable at the regional or local level. The sheer volume of data alone cannot overcome issues of potential bias and, in some cases, can magnify them[10,11].

These challenges point to a greater role for authors of global studies in harmonizing their research outcomes with regional needs and priorities. Strategies for aligning research that makes use of the large number of contributing authors could involve consultation with natural resource managers or the use of regional focus groups to identify errors and inconsistencies. In this case, examination of the substantial body of publicly available, annually published status reports for the relevant Australian fisheries, or engagement with Australian fisheries scientists, would have revealed the errors.

Big-data research driven by multi-author collaboration has reshaped the speed and scale at which science is conducted and delivered, with impact and reach often far exceeding traditional studies. The responsibility lies with practitioners to ensure that these methods are used appropriately given their potential to influence decision-making.

In Western Australia, the findings of Queiroz et al.[3] risk undermining confidence in the science-based management controls that are already implemented to protect the mature biomass of long-lived dusky shark (*Carcharhinus obscurus*) and sandbar shark (*C. plumbeus*) stocks in the region[12]. Off the southern Great Barrier Reef, the incorrect identification of a global longlining hotspot has the potential to undermine regional advice for the conservation of tiger sharks (*Galeocerdo cuvier*) and white sharks (*Carcharadon carcharias*), which have seen major population declines over recent decades[13].

The demand for solutions to global-scale environmental problems has necessitated changes to the prevailing culture of individual, investigator-driven ecology[14]. Queiroz et al.[3] provide a powerful demonstration of what can be achieved when ecologists work collectively by leveraging their data and expertise to approach these problems in new ways. An ongoing challenge of this and similar studies is how to provide globally relevant advice without superseding that of practitioners working at the regional level. A balanced and critical view of highly collaborative and data-intensive approaches is essential if the opportunities they provide are to be fully realized.

Reporting summary

Further information on research design is available in the Nature Research Reporting Summary linked to this paper.

Data availability

The results of the manual vessel review are available on GitHub (https://github.com/alharry/sharkMA).

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Author contributions A.V.H. carried out the analysis and wrote the first draft. A.V.H. and J.M.B. conceived the idea, interpreted the results, and edited and revised the final manuscript.

Competing interests The authors declare no competing interests.

Additional information
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Reporting Summary

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Data were downloaded from Global Fishing Watch
Data analysis	All data analysis was carried out using R

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Processed fishing vessel movement data presented in Figure 1 were downloaded from Global Fishing Watch [https://globalfishingwatch.org/; accessed 6th August 2019]. The results of the manual vessel review summarized in Table 1 are available on GitHub [https://github.com/alharry/sharkMA].

Field-specific reporting

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Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study involved a manual review of fishing vessel movement data used in the spatial risk assessment of industrialized fishing by Queiroz et al. 2019: [https://doi.org/10.1038/s41586-019-1444-4].
Research sample	Longline and purse seine fishing vessel movement data from the Global Fishing Watch database were manually reviewed.
Sampling strategy	No sampling was undertaken.
Data collection	Data were downloaded from Global Fishing Watch.
Timing and spatial scale	The timing and spatial scale are described in full in the Supplementary Methods.
Data exclusions	All data were included.
Reproducibility	No experiments were conducted. Data used in the study are available from Global Fishing Watch.
Randomization	Randomization is not relevant to this type of study.
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☒	☐	ChIP-seq
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☒	☐	MRI-based neuroimaging

Reply to: Caution over the use of ecological big data for conservation

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REPLYING TO A. V. Harry & J. M. Braccini *Nature* https://doi.org/10.1038/s41586-021-03463-w (2021)

Our global analysis[1] estimated the overlap and fishing exposure risk (FEI) using the space use of satellite-tracked sharks and longline fishing effort monitored by the automatic identification system (AIS). In the accompanying Comment, Harry and Braccini[2] draw attention to two localized shark–longline vessel overlap hotspots in Australian waters, stating that 47 fishing vessels were misclassified as longline and purse seine vessels in the Global Fishing Watch (GFW)[3] 2012–2016 AIS fishing effort data product that we used. This, they propose[2], results in misidentifications that highlight fishing exposure hotspots that are subject to an unexpected level of sensitivity in the analysis and they suggest that misidentifications could broadly affect the calculations of fishing exposure and the central conclusions of our study[1]. We acknowledged in our previously published paper[1] that gear reclassifications were likely to occur for a small percentage of the more than 70,000 vessels studied, however, here we demonstrate that even using much larger numbers of vessel reclassifications than those proposed by Harry and Braccini[2], the central results and conclusions of our paper[1] do not change.

In our use of a third-party dataset such as GFW[3], we stated clearly[1] that the dataset is undergoing continuous refinement to correct for acknowledged contamination of some gear types with others in some regions (for example, drifting longlines with bottom-set longlines off New Zealand[1]). The characterization of GFW vessels (gear) is undertaken using two convolutional neural networks that were trained[3] on 45,441 marine vessels (fishing and non-fishing) that identified six

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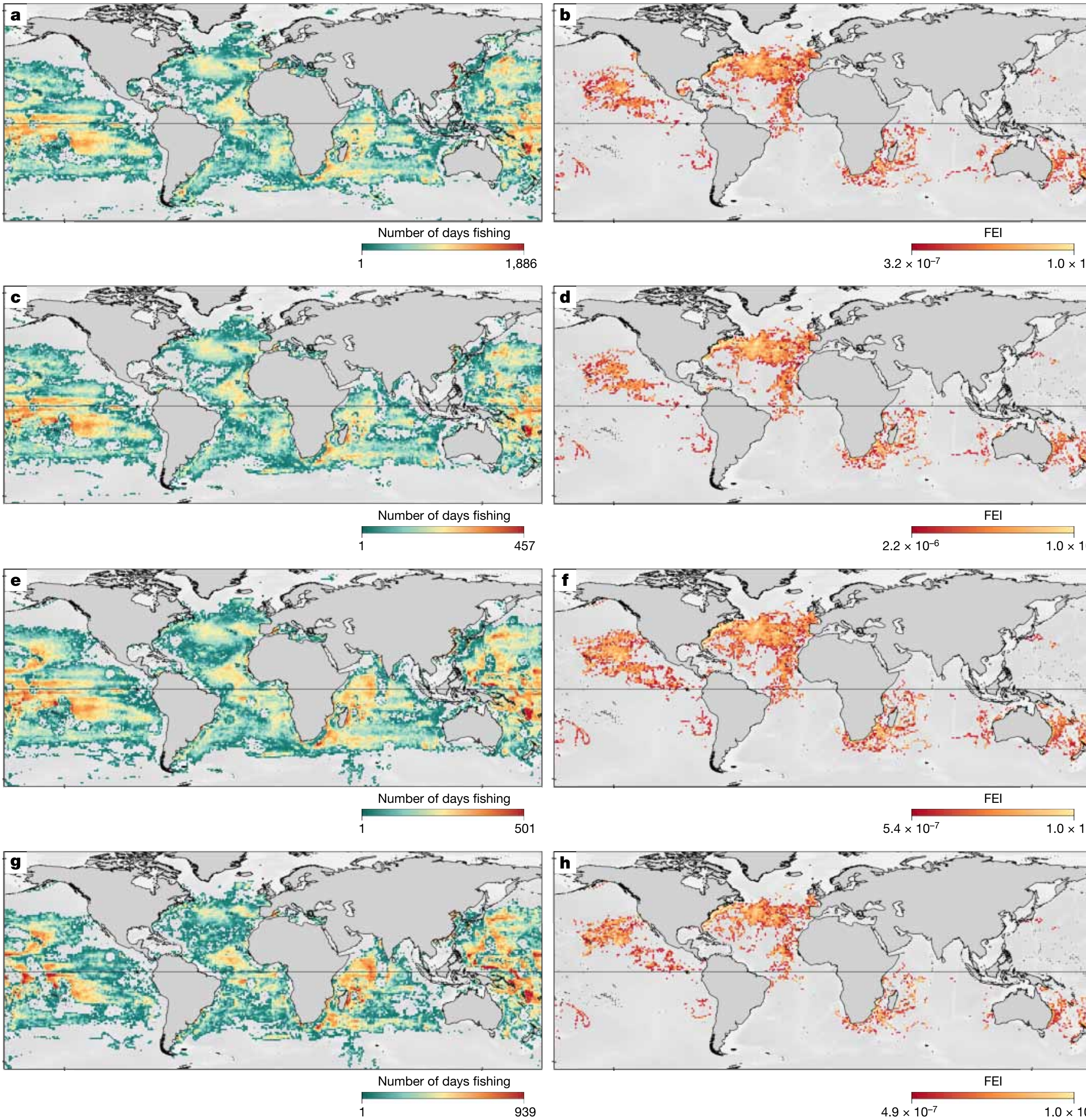

Fig. 1 | Comparing AIS longline fishing datasets. a–h, Comparison of GFW data of AIS longline fishing effort (**a**, **c**, **e**, **g**; fishing days, where 1 day = 24 h fishing effort) and spatial overlap intensity (FEI) with pelagic sharks (**b**, **d**, **f**, **h**) for three GFW datasets of longline fishing effort and Queiroz et al.[1]. The original 2012–2016 AIS longline fishing effort and FEI (**a**, **b**) was compared with the new data releases of GFW fishing effort for 2012–2016 (**c**, **d**), 2012–2018 (**e**, **f**) and 2018 only (**g**, **h**). These analyses show minor global differences across the datasets even in the light of improvements in gear characterization algorithms and further verification with additional fishing vessel metadata.

classes of fishing vessels and six classes of non-fishing vessels with 95% accuracy, as stated in our paper[1]. It is inevitable, therefore, that for some of the more than 70,000 AIS-monitored fishing vessels analysed, the gear was misclassified. Fortunately, a growing number of nations now maintain publicly accessible, online vessel registries to promote transparency and science within the fishing sector. For example, the European Union (EU) releases identifying information (including vessel name, identification numbers and fishing gear) for all fishing vessels registered to any EU country[4]. This eliminates the need to develop and refine models to estimate this information, as was the case for most of the vessels that we analysed. For countries that have not adopted this practice, including Australia, models provide necessary estimates in lieu of official information.

Since the publication of our paper[1] there have been further improvements, including the recent data of AIS longline fishing effort for 2018 with updated gear assignments based on convolutional neural networks and data for more vessels. Mapping the new data (Fig. 1) shows that, indeed, the fishing effort by 12 vessels in Australia's Northwest Shelf

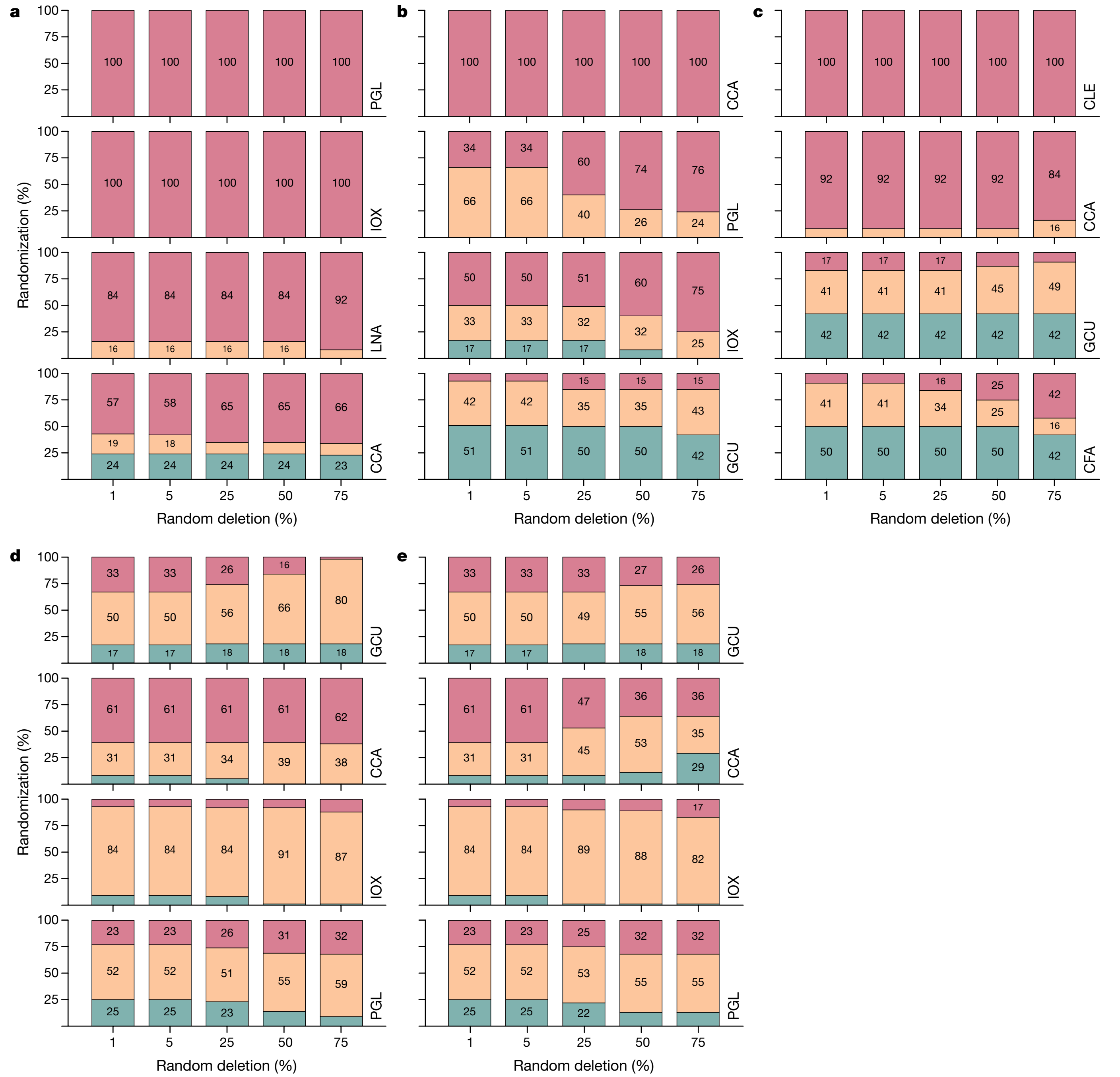

Fig. 2 | Example effects of random deletions of fishing effort data on exposure risk patterns. a–e, The percentage of randomized deletions from 100 repeats that resulted in a species exposure risk estimate occurring within the high (red), moderate (yellow) or low (green) risk category at each level of deletion (1%, 5%, 25%, 50% or 75%) of fishing effort grid cells per sub-region. **a**, North Atlantic. **b**, Eastern Pacific Ocean. **c**, Southwest Indian Ocean. **d**, Northwest Oceania. **e**, Eastern Oceania. The map that shows the locations of sub-regions is provided in Supplementary Fig. 1. CCA, white shark (*Carcharodon carcharias*); CFA, silky shark (*Carcharhinus falciformis*); CLE, bull shark (*Carcharhinus leucas*); GCU, tiger shark (*Galeocerdo cuvier*); IOX, shortfin mako shark (*Isurus oxyrinchus*); LNA, porbeagle shark (*Lamna nasus*); PGL, blue shark (*Prionace glauca*). Overall, only 6 out of 36 species–region combinations (16.7%) showed significant differences in the proportion of 100 randomizations per combination that each resulted in exposure risk falling within higher, moderate and lower risk categories when comparing 1% and 75% of random deletions of fishing effort data. Detailed summaries are provided in Supplementary Tables 1–7.

(NWS) is now removed, indicating that these few longline and purse seine vessels were not classified accurately in the GFW 2012–2016 data product. However, the GFW 2018 product does not show the reclassifications proposed off the southern Great Barrier Reef (GBR); therefore, further verifications are needed to correct those.

We agree that the space use hotspot for tiger shark (*Galeocerdo cuvier*) in Australia's NWS does not overlap with AIS-monitored longline fishing effort in that area based on the GFW 2012–2016 data product that we used. Therefore, an important question raised[2] is whether the reclassification of the gear types of 47 vessels directly affects the calculations of fishing exposure and our conclusions. In our paper[1], the area (at the 1° × 1° grid cell scale) covered by AIS longline fishing effort in Western Australia is 0.4% of the global coverage and the southern GBR area represents only 0.06%. Within the Oceania region used in our paper, Western Australia comprises 2.2% and GBR 0.35%. Therefore, the areas comprising reclassifications provide a minor contribution to the spatial overlap and FEI values that we calculated not only globally but also within the Oceania region.

To check our results within the global context, we compared the spatial overlap of sharks and longline fishing effort in our paper[1] with the new releases of GFW fishing effort data that have been made available since the publication of our paper (Fig. 1 and Extended Data Table 1). The new releases of GFW data take into account refinements in the algorithms used to classify vessel (gear) types and new knowledge from metadata on the gear of the vessels. We find that—globally—the GFW longline fishing patterns remain almost identical (Fig. 1). Spatial overlap and exposure patterns also remain very similar. For example, the mean monthly spatial overlap estimate for all oceans of 24% presented in our paper is within the range (19–29%) calculated using the new GFW data (Extended Data Table 1). In the Exclusive Economic Zone (EEZ) of Australia, the number of FEI grid cells actually increased from 151 to 155 between the original GFW data (2012–2016) and the updated 2012–2018 data, whereas in the EEZ of western Australia the number decreased from 50 to 37 grid cells between datasets. For Oceania (including Australian shelf waters), the spatial overlap of 24% in our paper is within the 17–25% range estimated with newer GFW data. We also find that the spatial overlap–FEI plots remain largely unchanged across the four GFW datasets (Extended Data Fig. 1). Therefore, the NWS vessel reclassifications are minor and affect a single hotspot for tiger sharks.

To address the potential issue raised by Harry and Braccini[2] that longline vessel reclassifications occur more broadly and may alter results in substantial ways, we randomly deleted 1% of grid cells that contained longline fishing effort per ocean region to simulate reclassification of longline vessels to other gears and this randomization was repeated 100 times. This is more extreme than simply removing a few individual vessels because each replicate removes 1% of grid cells, each comprising summed fishing effort from single or multiple vessels. Extended Data Table 2 shows that of the 30 species–region pairs available for analysis, we found that only 7% of species–region pairs changed from highest (red) to moderate (yellow) fishing exposure risk, whereas 3% changed from moderate to highest risk after the simulated 'reclassification'. We repeated this for 5% random deletions. Even at this much higher level of longline gear reclassification, we obtained the same results (Extended Data Table 3).

To examine what level of localized reclassification may lead to a breakdown of the fishing exposure risk patterns that we found, we randomly deleted 1%, 5%, 25%, 50% and 75% of fishing effort grid cells within five sub-regions (Supplementary Fig. 1) and recalculated spatial overlap and FEI for four key species per sub-region (Fig. 2 and Supplementary Methods). Results reveal no change in patterns of overlap and FEI for the four key species for the random deletion of up to 75% of data for regions in which shark spatial densities and fishing effort were both high and spatially extensive (for example, the North Atlantic (Fig. 2a)). Patterns change marginally above deletion of 25% of data for some species in other sub-regions in which fewer vessels and sharks were tracked (Fig. 2b, d). Seasonal patterns in exposure risk also remained largely unchanged albeit with larger differences at higher levels of fishing effort deletions (Supplementary Fig. 2). Levels of inaccuracy as high as we simulated in these tests are not evident in worldwide GFW vessel classifications[3]. Clearly, our results are not as sensitive to minor changes in sub-region vessel reclassifications as suggested by Harry and Braccini[2].

Harry and Braccini[2] emphasize that regional results should not be overlooked within a global-scale study. We agree, which is why we provided region-specific results for individual species that were discussed in detail in our paper[1] (see supplementary results and discussion 2.6 of ref. [1]), in which each regional analysis was informed by regional experts among the authorship, including for Western Australia. Although continued refinements to fishing gears ascribed to AIS-monitored vessels in the GFW dataset are useful, we disagree with Harry and Braccini[2] about the levels of fishing threatening large sharks in Australia's NWS where we identified the space use hotspot for tiger sharks. They incorrectly assert that longline fishing has not occurred for two decades in Australia's NWS[2]. Longline and gillnet fishing not only occurred historically in the NWS and offshore to the boundary of Australia's EEZ[5], but also continues to occur there through illegal, unreported and unregulated fishing[6–8] by vessels that are not equipped with or that do not use AIS, which we discussed in our paper[1]. Illegal, unreported and unregulated fishers are known to target sharks—including tiger sharks[9]—for fins, an ongoing threat that has been a major problem in Australia's NWS[7], which overlaps with the tiger shark hotspot[8]. Therefore, it cannot be discounted that the shark hotspot overlaps with non-AIS monitored fishing activity, especially as more than 0.5 million km^2 of the NWS remains open to commercial shark fishing[10]. Furthermore, the 55-year-long shark control program along 1,760 km of coastal northeastern Australia shows a long-term decline in the abundance of tiger sharks[11,12]; this is a region with movement and genetic connectivity with tiger sharks of the NWS[13]. In our view, Harry and Braccini[2] overlook existing threats to tiger sharks and other shark species from fishing in the NWS.

As a consequence, we disagree with the opinion that existing science-based management has been undermined by our results or conclusions. Rather, in our paper[1] we highlighted specifically the need to incorporate tracking and other spatial data into scientific assessments. However, this should not be misinterpreted as spatial data representing a regional management tool to replace assessments that rely on other types of data, such as time-series catch data. Indeed, a review[14] cited in our paper identifies examples in which marine animal tracking and space use data informed policy, and it is evident that these data were never used in isolation from existing management regimes or complementary scientific assessments. Our paper[1] emphasizes the need for a holistic approach to shark management that should also incorporate dynamic, spatial data.

Reporting summary

Further information on experimental design is available in the Nature Research Reporting Summary linked to this paper.

Data availability

Data used to prepare the maps (shark relative spatial density, longline-fishing effort and shark–longline-fishing overlap and FEI) are available on GitHub (https://github.com/GlobalSharkMovement/GlobalSpatialRisk).

Code availability

Code used to prepare the maps (shark relative spatial density, longline-fishing effort and shark–longline-fishing overlap and FEI) is available on GitHub (https://github.com/GlobalSharkMovement/GlobalSpatialRisk).

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Author contributions N.Q. and D.W.S. planned the data analysis. N.Q. led the data analysis with contributions from M.V. and D.W.S. N.E.H. contributed analysis tools. D.W.S. led the manuscript writing with contributions from N.Q., N.E.H. and all authors. Seven of the original authors were not included in the Reply authorship; two authors retired from science and the remaining five, although supportive of our Reply, declined to join the authorship due to potential conflicts of interest with the authors of the Comment and/or their institutions.

Competing interests The authors declare no competing interests.

Additional information
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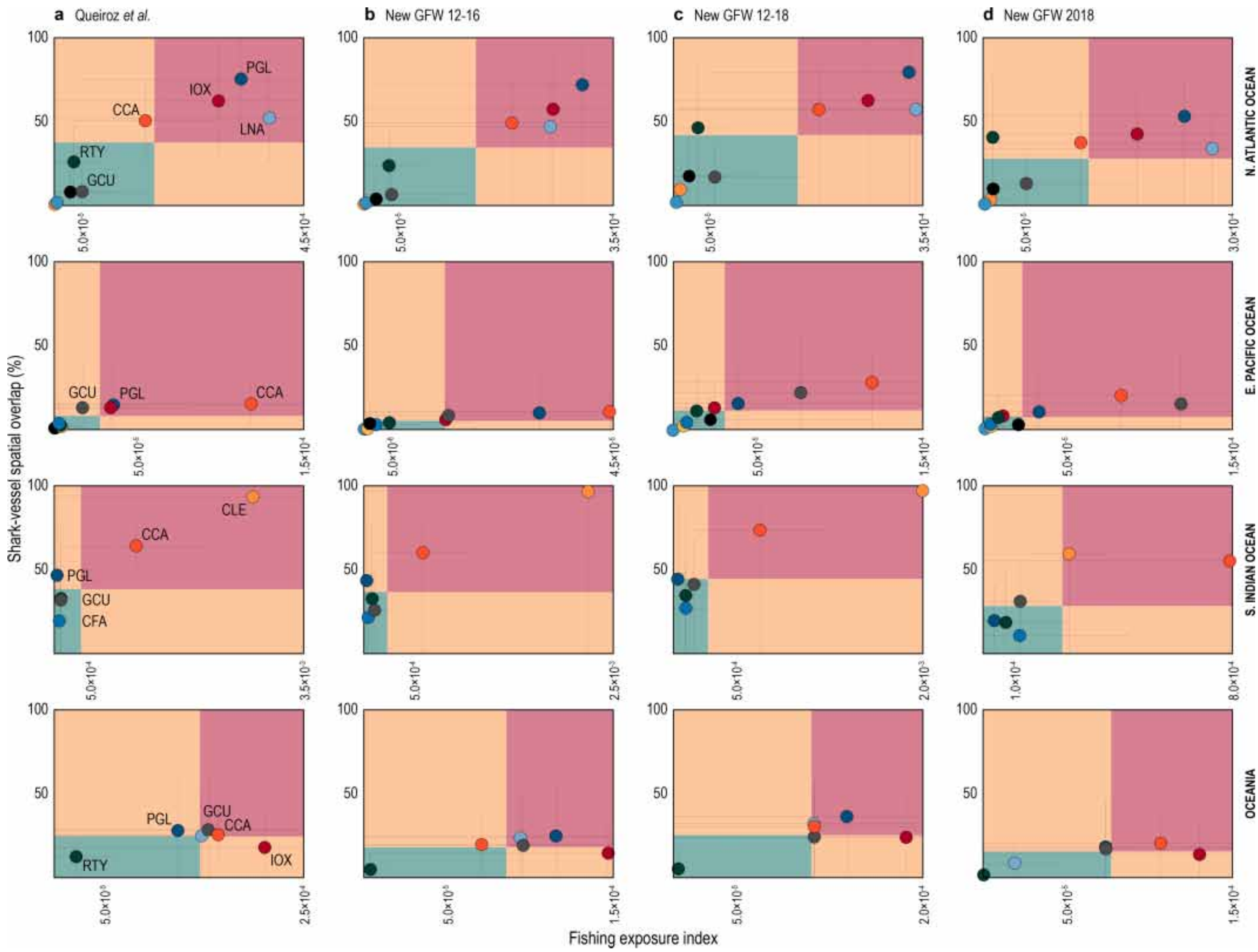

Extended Data Fig. 1 | Comparing shark exposure risk between AIS longline fishing effort datasets. a–d, Estimated exposure risk of sharks to capture by GFW AIS longline fishing effort across ocean regions for Queiroz et al.[1] (**a**) compared with three improved data releases since the paper was published (**b**–**d**). The plots show minor effects of any changes on estimates of shark exposure risk from AIS longline fishing effort and confirm the global results and conclusions of our paper. **a**, Data from Queiroz et al.[1]. **b**, Data from GWF 2012–2016. **c**, Data from GWF 2012–2018. **d**, Data from GWF 2018.

Extended Data Table 1 | Mean monthly spatial overlap estimates (%) of pelagic shark space use and AIS longline fishing effort for different AIS datasets

	N tags	Queiroz et al.		New GFW 2012-16		New GFW 2012-18		New GFW 2018	
		mean	S.D.	mean	S.D.	mean	S.D.	Mean	S.D.
Global	1611	24.37	33.08	21.98	32.20	28.93	34.44	18.98	25.79
N Atlantic	649	37.41	38.60	34.62	37.58	42.00	38.21	27.92	29.09
E Pacific	588	7.80	15.99	5.18	13.29	11.38	19.14	7.53	14.89
SW Indian	153	38.31	35.31	36.69	35.14	44.53	36.95	28.38	28.20
Oceania	151	24.42	27.21	18.13	25.18	25.32	29.04	15.61	23.21

Extended Data Table 2 | Effect of 1% random deletion of fishing effort grid cells within each region on risk exposure estimates

	N Atlantic		E Pacific		SW Indian		Oceania	
Main species	Before	After	Before	After	Before	After	Before	After
Prionace glauca	Red	Red	Red	Yellow	Yellow	Yellow	Yellow	Yellow
Isurus oxyrinchus	Red	Red	Red	Red			Yellow	Yellow
Lamna nasus	Red	Red					Yellow	Green
Carcharodon carcharias	Yellow	Red	Red	Red	Red	Red	Red	Red
Galeocerdo cuvier	Green	Green	Yellow	Green	Green	Green	Red	Yellow
Sphyrna spp.	Green	Green	Green	Green				
Rhincodon typus	Green	Green	Green	Green	Green	Green	Green	Green
Carcharinus longimanus	Green	Green	Green	Green				
Carcharhinus falciformis			Green	Green	Green	Green		
Carcharhinus leucas	Green	Green			Red	Red		
Lamna ditropis			Green	Green				

The results show minor effects of substantial removal of longline fishing effort. Before/after denotes before/after deletion. Red denotes the highest risk exposure category, green indicates the least risk. The 'after' colour represents the category with the highest percentage of occurrence after 100 randomizations. No change in colour between before/after indicates no change in spatial overlap and exposure risk of species from AIS longline fishing effort. White indicates that no tracking data are available to undertake analysis. There are no changes from high to low, or vice versa.

Extended Data Table 3 | Effect of 5% random deletion of fishing effort grid cells within each region on risk exposure estimates

	N Atlantic		E Pacific		SW Indian		Oceania	
Main species	Before	After	Before	After	Before	After	Before	After
Prionace glauca								
Isurus oxyrinchus								
Lamna nasus								
Carcharodon carcharias								
Galeocerdo cuvier								
Sphyrna spp.								
Rhincodon typus								
Carcharinus longimanus								
Carcharhinus falciformis								
Carcharhinus leucas								
Lamna ditropis								

The results show minor effects of substantial removal of longline fishing effort. Before/after denotes before/after deletion. Red denotes the highest risk exposure category, green indicates the least risk. The 'after' colour represents the category with the highest percentage of occurrence after 100 randomizations. No change in colour between before/after indicates no change in spatial overlap and exposure risk of species from AIS longline fishing effort. White indicates that no tracking data are available to undertake analysis. There are no changes from high to low, or vice versa.

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Software and code

Policy information about availability of computer code

Data collection	No data collection software was used.
Data analysis	All analyses described were undertaken in R.

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Data and source code used for preparing figure maps (shark relative spatial density, longline-fishing effort and shark–longline-fishing overlap and FEI) are available on GitHub (https://github.com/GlobalSharkMovement/GlobalSpatialRisk).

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Ecological, evolutionary & environmental sciences study design

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Study description	This study is a Reply to a Matters Arising comment on our original paper. To answer the points raised we re-plotted some of the original shark movements and fishing effort data in our paper which are fully described in figure and table legends and in the original paper. We also carried out new analyses using newer data releases of global longline fishing effort data that were freely available from Global Fishing Watch (www.globalfishingwatch.org).
Research sample	In this Reply, the additional data used were the Global fishing Watch updated data release for AIS-monitored longline fishing effort in 2012-2018.
Sampling strategy	Global longline fishing effort data were obtained for automatic identification system (AIS) monitored vessels >300 gross tons.
Data collection	Global longline fishing effort data for automatic identification system (AIS) monitored vessels >300 gross tons were made available by the Global Fishing Watch.
Timing and spatial scale	Global for 2012-2018.
Data exclusions	No relevant data were excluded.
Reproducibility	No experiments as such were conducted, rather our data are based on satellite tracked movements of individual pelagic sharks and fishing vessels.
Randomization	Randomization procedures were used when removing 1, 5, 25, 50 and 75% of the AIS data for breakpoint sensitivity analysis. Methods are fully described in the Reply and Supplementary Information files.
Blinding	Blinding is not relevant to this type of study because our original data were based on movements of wild animals and fishing vessels.

Did the study involve field work? ☐ Yes ☒ No

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Methods

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☒	☐	ChIP-seq
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