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1 Climate change drives poleward increases

2 and equatorward declines in marine species

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Summary

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Marine environments have increased in temperature by an average of 1°C since pre-industrial (1850) times [1]. Given that species ranges are closely allied to physiological thermal tolerances in marine organisms [2], it may therefore be expected that ocean warming would lead to abundance increases at poleward side of ranges, and abundance declines towards the equator [3]. Here we report a global analysis of abundance trends of 304 widely distributed marine species over the last century, across a range of taxonomic groups from phytoplankton to fish and marine mammals. Specifically, using a literature database we investigate the extent that the direction and strength of long-term species abundance changes depend on the sampled location within the latitudinal range of species. Our results show that abundance increases have been most prominent where sampling has taken place at the poleward side of species ranges, while abundance declines have been most prominent where sampling has taken place at the equatorward side of species ranges. These data provide evidence of omnipresent large-scale changes in abundance of marine species consistent with warming over the last century, and suggest that adaptation has not provided a buffer against the negative effects of warmer conditions at the equatorward extent of species ranges. On the basis of these results we suggest that projected sea temperature increases of up to 1.5°C over pre-industrial levels by 2050 [4] will continue to drive latitudinal abundance shifts in marine species, including those of importance for coastal livelihoods.

Results and Discussion

Marine organisms have a temperature range outside of which physiological processes cease to be optimal. As such, species distributions often correspond closely with physiological temperature limits [2, 5]. Cold tolerance can determine the position of the poleward edge of a species range, and consequently, ocean warming is expected to increase organismal performance, survival and reproductive success at higher latitudes of species ranges. It has therefore been predicted that warming seas should also drive increases in the abundance of species at their poleward range side [6]. Equally, warm tolerance is strongly associated with the position of the equatorward edge of marine species ranges. Hence, as oceans warm we may expect to find reductions in performance, survival and recruitment at lower latitudes of species ranges, leading to reductions in abundance at equatorward range limits [4].

Importantly, however, space use by marine species is not simply determined by thermal affinities. Species distributions and abundances are also dependent upon availability of core ecological resources such as food and substrate, which are not homogenously distributed across species ranges. Consequently, distributions of species may not be fully predicted on the basis of the thermal environment and physiological tolerances alone [7]. Moreover, the temporal population-abundance response of species to warming at any position in their range may not exclusively depend on their thermal physiology, but also the responses of the species with which they interact [8]. An additional consideration is that regional temperature shifts are not the only physical changes in the marine environment associated with climate change, as parallel changes to storminess [9, 10], salinity [11], acidification [12] and sea ice conditions [13] have also been reported. To fully understand abundance changes of populations requires a comprehensive understanding of marine environmental change, as well as the physiological, life history and ecological characteristics of study species [14].

Despite the intrinsic complexities of marine biological systems, analyses from local and regional datasets suggest that thermal affinities are strong predictors of the responses of marine species to increasing temperatures [15, 16]. In general, studies have reported that within local communities warm-adapted species have increased in abundance, relative to cool-adapted species that have declined in abundance [2, 6, 15, 16]. However, such studies tend to be limited to a small number of species and a single locality or region. A more complete understanding of large-scale patterns of climate-associated local abundance change requires combining information from multiple studies across broad taxonomic diversity, and across wider spatial scales that encompass the full realised latitudinal distributions of study species [17]. In the most comprehensive analyses of marine species to date, abundance responses

have been interpreted as being at poleward and equatorward limits [2] or "consistent" or "inconsistent" with climate change [17] based on the findings of the original authors. However, a fully quantitative approach is required to test the strength of evidence for species-level poleward abundance increases and equatorward abundance declines within marine systems over the last century. Here, we consider abundance trends of marine species over the last century within an explicit latitudinal and quantitative framework.

We extracted all single-species abundance change observations from a published meta-database covering literature published from 1991 to 2012 [17], and added further records published from 2012 to 2016. For each record we ensured the direction of abundance change during the study was recorded (either positive or negative, with respect to time or temperature), and ensured each record had an accompanying survey location (Figure 1A). We then identified the relative latitudinal position of the survey location within the known latitudinal distribution of the species, as determined from occurrence data within the Global Biodiversity Information Facility (GBIF) database [18]. In total the complete dataset included 540 records of abundance change, across 304 species (average 1.67 records per species; range 1 to 21) ranging from phytoplankton and macroalgae, to seabirds and marine mammals (Figure 1B). We then used these data to generate linear models that examined how the direction of abundance change was dependent on the latitudinal position of the survey, and if there were any biases in responses associated with hemisphere of study or the survey methods (i.e. time-span of study, and whether the study was a continuous time series, an irregularly sampled study, or a two-point comparison).

Analyses based on our complete dataset of 540 sets of records demonstrated that the location of sampling within the species range was a highly significant predictor of the direction of abundance change (Table S1). Specifically, marine species were significantly more likely to have increased in abundance if a study had been undertaken at the poleward range side than at the equatorward range side. By contrast species were significantly more likely to have declined in abundance if a study had been undertaken at the equatorward side than the poleward range side (Figure 2A). We found no influence of survey methods or hemisphere of the study (Table S1). We repeated analyses on a subset of the dataset where the original authors report a statistically significant change in abundance over the study period (185 from 540 records), and again we found the position in the latitudinal range of the species to be the most important predictor of the direction of abundance change (Figure 2B). Next, we explored the strength of abundance responses to temperature (or year) using the reported correlation coefficients (*r* values) that were available for 77 from 540 records. Again, we found greater

negative responses occurring at the equatorial range margins and more positive responses at the polar side of species distributions (Figure 2C).

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Our study relies on published abundance trends being unbiased representations of abundance changes in the natural environment. However, there is a possibility that observations of significant abundance change matching expectations from climate change are more likely to be selected for publication [19]. This effect is plausibly strongest in singlespecies studies [17], which comprised 68 records in our analysis, so we repeated analyses on only the 472 records from multispecies studies. Our analyses were robust with respect to potential publication bias, with position of the study within the latitudinal range again the strongest predictor of the direction of abundance responses in the multispecies analysis (Table S1). The reported observations in our dataset are spatially clustered, with the majority of observations (448 of the 540 records) from the Northern Hemisphere, and were concentrated in the temperate continental shelf waters of Europe, North America and Japan (Figure 1A). To investigate potential influence of spatial bias we subsampled the data to exclude records that were in close spatial proximity to other records from the same species (within the same 1 degree latitude × longitude grid cell). The analysis of this spatially thinned dataset (478 of the 540 records) again resolved latitudinal position of the study within the range of the species as the most reliable predictor of the direction of abundance change. Taken together these analyses indicate the data are robust to publication and spatial biases, however further work is required across undersampled regions and taxonomic or functional groups to fully understand the global extent of the observed pattern.

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Addressing taxonomic bias, we explored if survey position in the species range was a consistent predictor of species responses among each of the five taxonomic or functional groups that were most well represented in the dataset, namely non-larval fishes, larval bony fishes, seabirds, benthic invertebrates, and zooplankton (Figure 1B). Although we found that the extent of the response varied significantly among these groups (Table S2), we found a consistent pattern of observed abundance increases at the poleward side of species range, and decline at equatorward sides in all taxonomic groups. This pattern was statistically significant in individual analyses of non-larval fishes, larval bony fishes and seabirds (P < 0.05, Table S2), with larval bony fishes having a more pronounced positive response at the poleward side of their range relative to other groups (Table S2, Figure 3). This result highlights variation among marine organisms (and potentially their varied life stages) in their responses to warming. Differences among taxonomic or functional groups may be expected due to variation in life history traits including reproductive rates, dispersal biology, migratory

behaviour and growth rates [14], which in turn affect opportunities to maximise on ecological opportunity.

Clearly not all species and populations followed the general pattern, and such contrasts in responses to warming may be predicted in situations where thermal constraints are not necessarily the primary determinant of species ranges. Such situations can arise when the other physiological (e.g. oxygen availability) or ecological (e.g. food availability) constraints dominate, although such constraints often covary with temperature (e.g. [20]). Equally, there are situations where the latitudinal limit of a species is determined by a geographic barrier such as the presence of a continental landmass, or the absence of suitable substrate to colonise [21], rather than the thermal environment. Finally, the abundance of many species will also have been influenced by human activities in recent history, such as habitat degradation and fisheries, which may have already influenced population sizes and limited capacity for rapid response to climate warming [22].

We focused on latitudinal range limits of species, making the broad assumption that latitudinal gradients correspond with the thermal gradients that species occupy. However, while global thermal gradients are broadly colder towards the poles, a range of factors influence local temperature variation across latitude, depth and time. For example, surface ocean currents and upwelling can drive variation in associations between latitude and temperature [23]. Equally, the pace of climate change is not homogeneous and can be inconsistent with latitudinal gradients [21, 24]. Although we found an overall association between time and temperature across all survey locations in this dataset, it is possible that abundance changes are more likely to be detected where the pace of climate change has been most rapid [25].

A notable result of this study was that populations at both polar and equatorial range margins are undergoing abundance changes. This is consistent with expectations that marine species have shifted abundance in line with their full thermal tolerance limits [2], and is important because it is suggestive of thermal tolerance limits of species being relatively inflexible over decadal timescales. Specifically, it also indicates that populations of marine organisms at the equatorial sides of species ranges are unable to adapt at a sufficiently rapid pace to enable them to thrive in warmer conditions. Evolutionary adaptation to warming conditions may be particularly slow for species with relatively long generation times such as the marine fishes [26] which dominate our dataset, but by contrast evolutionary adaptation may be expected to be more rapid in taxonomic or functional groups with fast life histories such as phytoplankton [27]. It is also plausible that differential responses of marine species to warming will result in

abundance shift mismatches between interdependent components of marine communities, for example predators and their prey [28].

We included a wide breadth of studies from across the globe, but ideally more records would be available from under-represented taxonomic or functional groups, including those of ecological and commercial importance. Additionally, the available data was strongly biased towards temperate latitudes and further work is needed to determine whether the same patterns hold for tropical species. With increased recognition of the value of long-term and resurvey data, increasing numbers of datasets are becoming available through initiatives to study broader patterns of biodiversity change [29, 30]. There are also efforts to bring together and standardise existing datasets over space and time, to enable abundance change estimates to be made across vast expanses of marine habitat [31]. Thus, it is possible that future analyses will be able to evaluate temporal abundance changes across much larger proportions of species ranges than are considered here, enabling a more thorough evaluation of how physiological, ecological, and life history traits interact with environmental variation to drive abundance changes within individual species.

In conclusion, the analyses presented here clearly demonstrate a pattern of local abundance change that is widespread in marine systems, most likely due to the combination of physiologically-determined thermal niches and changes in climatic variables. Thus, our study builds on evidence of climate-associated local abundance changes and sits alongside climate-driven changes in other biological parameters such as the overall distributions of species, and shifts in the timing of life history events [2]. Average sea surface temperatures are set to rise further over the course of this century [4] and the frequency of marine heatwaves is increasing [32]. It therefore seems plausible that local abundance changes linked to physiological and ecological tolerances will continue to take place at both the poleward and equatorward sides of species ranges impacting further on local marine assemblages and the coastal industries that depend on them.

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Author Contributions

- 214 Conceptualization, M.J.G.; Data compilation, L.A.R., J.J.F. and R.A.H.; Methodology, R.A.H.,
- 215 L.A.R., R.A.C and M.J.G.; Formal analysis, R.A.H., L.A.R., R.A.C and M.J.G.; Writing -

- Original Draft, L.A.R., R.A.H. and M.J.G.; Writing Review & Editing, L.A.R., J.J.F., R.A.C.,
- 217 S.D.S., M.J.G.; Funding Acquisition, M.J.G. and S.D.S.

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Declaration of Interests

220 The authors declare no competing interests.

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Main text figure/table legends

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- Figure 1 Spatial and taxonomic coverage of studies analysed.
- A) Global distribution of long-term abundance observations used in this analysis. B) Number
- of temporal abundance records analysed in each of the nine taxonomic or functional groups
- (total n=540). Map relief data from the ETOPO1 Global Relief Model [41]. Photos represent
- 228 species in the dataset undertaking responses at range margins consistent with ocean
- warming: sea sparkle (*Noctiluca scintillans*) by M.A. Sampayo; common dolphin (*Delphinus*
- 230 *delphis*) original source anonymous; Australasian gannet (*Morus serrator*) by J.J. Harrison;
- lined chiton (Tonicella lineata) by M. Knoth; Atlantic salmon (Salmo salar) by H.-P. Fjeld.
- 232 Photos from Wikimedia commons licensed under the Creative Commons Attribution licences
- 2.3 2.0 (chiton), 2.5 (salmon) or 3.0 (sea sparkle, dolphin, gannet).

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- Figure 2. Long-term abundance changes depend on the position of sampling stations
- within the latitudinal range of species.
- 237 **A)** Abundance changes across all 540 records. **B)** Abundance changes recorded as significant
- in original data sources, 185 records in total. **C)** Reported *r* values for abundance change over
- time or temperature in original data sources, 77 records in total. The blue shaded area
- 240 indicates the 95% confidence interval, while vertical lines represent datapoints that reflect
- 241 either positive (1 in binomial model, shown as +1 on axis), or negative abundance changes (0
- in binomial model, shown as -1 on axis). See Table S1 for full model details.

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- 244 Figure 3. Associations between relative position in latitudinal range and direction of
- 245 the abundance change within each taxonomic/functional group.
- Abundance changes over the study time periods for A) Fish, B) Larval bony fish, C)
- Invertebrates (other), D) Seabirds, E) Zooplankton. These species groups represent the five
- 248 most well represented groups within the main dataset. The blue shaded area indicates the
- 249 95% confidence interval, while vertical lines represent datapoints that were either positive (1
- in binomial model, shown as +1 on axis), or negative (0 in model, shown as -1 on axis). See
- Table S2 for full model details.

STAR★Methods

Lead Contact and Materials Availability

Further information and requests for resources should be directed to and will be fulfilled by the Lead Contact, Martin Genner (M.Genner@bristol.ac.uk). This study did not generate new unique reagents.

Method Details

We sourced data on the abundance changes of marine species from two sources. First, we used the database generated by Poloczanska, et al. [17] that covered literature published between 1991 to 2012, and we extracted the records where abundance was the response variable. We then checked original papers to ensure observations were from fully marine species or species dependent on the ocean, and then also checked and assigned direction of the abundance response over the studied time interval. Secondly, we compiled observations from literature published between 2012 and 2016 using the same methodology as Poloczanska et al. [17]. For both sets of records we retained only those where abundance trends could clearly be attributed to individual species. Each study was defined as a continuous time series, an irregularly sampled study or a two-point comparison, as determined from the original paper. Studies were categorised as single-species (reporting trends for one species only) or multispecies (abundance trends for multiple species reported).

We included cases where abundance changes were correlated against time and cases where abundance changes were correlated against temperature. We quantified the association between time and temperature at study locations using the correlation coefficient (r) between year and mean annual sea surface temperature (SST). Mean annual SST was obtained for each latitude and longitude cell from monthly HadISST data, across every year of a study period [39]. This was performed for 139 of 157 unique locations, based on availability of consistent mean annual temperature data for the full study period. Overall, temperature and time were positively correlated in the locations and durations of the original studies, with an average correlation coefficient r = 0.34.

To assign positive or negative abundance trends for species at their study location, we used a three-step sequential process. First, and preferentially, where a study reported a statistically-significant abundance change, we used those records. Second, where significant responses were not recorded, but the direction of change was quantitatively described in the text, then those records were used. Third, where no quantitative assessment was provided in the text, but a visual image of the abundance data was available, we determined the trend

from the plotted data. In cases where abundance responses to both temperature and time were recorded, only the association with temperature analysis was included in analyses. Where the environmental variable reported was not explicitly temperature or time (e.g. sea ice), we ensured that the environmental variable was clearly associated with temperature or time by the original authors.

Occurrence data for each species were obtained from GBIF [18] via the ModestR tool [33]. A taxonomy for each species, from species to class rank is required for ModestR, and this was constructed using taxonomic information from the World Register of Marine Species (WoRMS) [38]. Any species that had been re-classified since the publication of the paper that the observation originated from were renamed in line with the accepted WoRMS taxonomy. ModestR was used to collate, visualise and check species occurrences from GBIF and to export the geographical coordinates associated with these records as text files (one file per species). We excluded 0,0 coordinates, occurrences falling on land, and duplicate coordinates to two decimal places. Where studies were conducted outside the recognised GBIF range they were assigned 1 for more poleward and 0 for closer to the equator to reflect the extreme range edge of the particular survey location.

Some species had occurrence records in both the northern and southern hemispheres. If the original survey location for a species in the database was undertaken in the Northern Hemisphere, we deleted from the dataset all coordinates from the Southern Hemisphere for that species, and vice versa. Species that were the focus of studies in both hemispheres were treated as two discrete entities, for example being referred to as "Species name N" and "Species name S". To avoid erroneous points or outliers having an undue influence on the species ranges, we removed 2% of the most extreme latitudinal records, 1% from each side of the range. We then checked resultant records visually for any remaining outliers, which were then deleted. To ensure latitudinal ranges were well characterised and reliable, any species left with fewer than 50 observations were excluded from further analysis. After these checks and deletions, we retained 540 abundance trend records from 304 species. Of these 540 trend records 185 were reported as significant in the original studies, and we generated a subset comprising only these significant record for some analyses due to the potential for non-significant trends to introduce type II errors in results.

To generate a spatially-thinned subset, we subsampled the 540 abundance trend records by removing repeat data for the same species within each 1° latitude and longitude grid cell. The dataset was first sorted by species and grid cell, and where two or more records of abundance change were reported the longest time series was retained (if records covered the same time

period, we systematically removed the first record in the data list). In total 62 records were removed from the full dataset to generate this spatially thinned subset of the data.

Quantification and Statistical Analysis

We calculated the relative latitudinal position of each study sampling location within the range of the focal species using the formula:

$$Sampling \ position \in species \ range = \frac{study \ latitude - equatorward \ extreme}{poleward \ extreme - equatorward \ extreme}$$

Where equatorward and poleward extremes were identified from the cleaned GBIF records, we modelled the association between the direction of the abundance change and predictor variables using Generalized Linear Mixed-Effects Model (GLMER-Model 1) with a binomial response with a link logit using the Ime4 package in R 3.6.0 [34, 40]. We used these models to analyse several data subsets including: the full dataset, only records with significant trends, only multispecies studies and spatially thinned data. In these models fixed effects included: sampling position in species range, study hemisphere, study timespan, and study type (continuous time series, irregular or two-point). Random effects included: taxonomic group (fishes, benthic invertebrates, larval fishes, macroalgae, mammals/reptiles, phytoplankton, seabirds, seagrass, zooplankton) and study (as multiple observations were typically reported in individual studies). Generalised linear models (GLM-Model 2) were subsequently used to generate simpler models with sampling position in species range as the sole predictor variable.

We modelled the association between reported r-values (including square-root transformed r^2 values) and the same set of predictor variables reported above using linear mixed-effects models (Model 3). We then used linear models (Model 4) with sampling position in species range as the sole predictor variable. The ImerTest package was used to extract output from mixed models. Model outputs were plotted using the effects package [36] (Fig. 2). R^2 values were obtained using the r2glmm package [35].

Data and Code Availability

All datasets and code are available at https://doi.org/10.6084/m9.figshare.11848152

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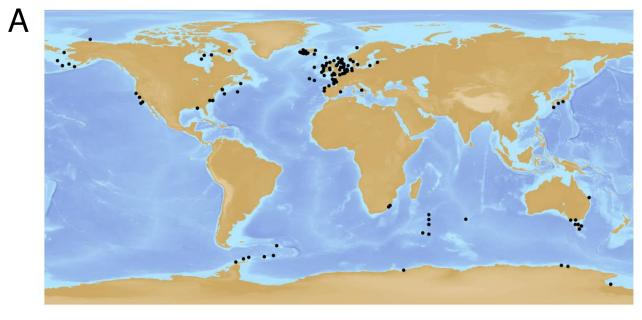
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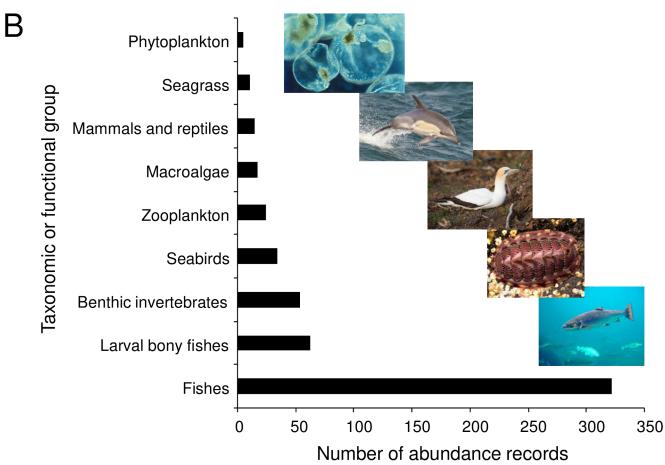
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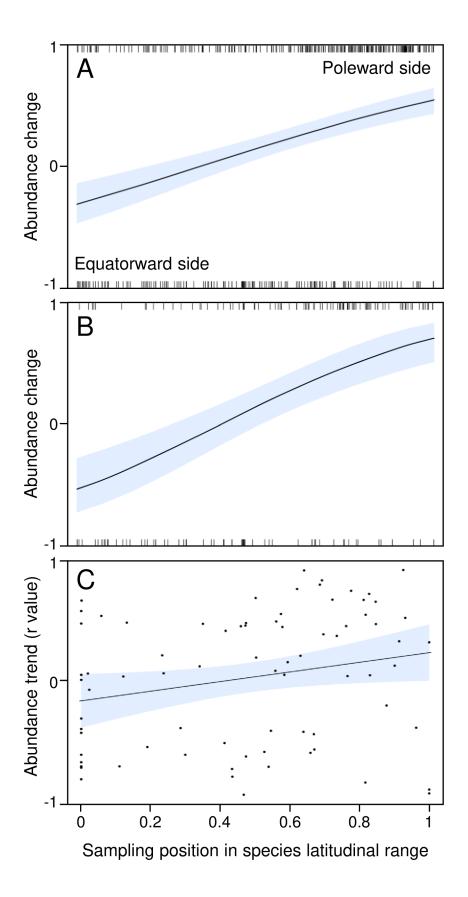
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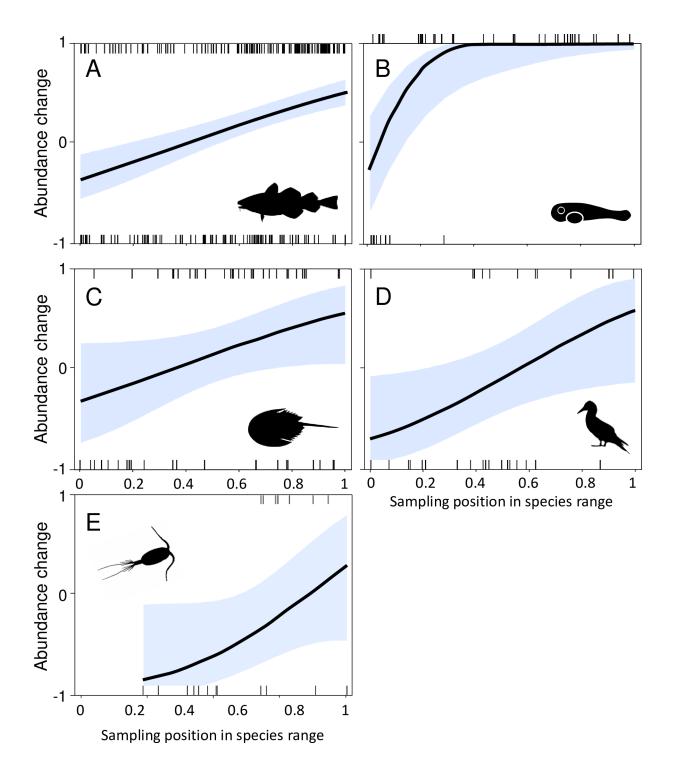
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Key Resources Table

RESOURCE	SOURCE	IDENTIFIER
Deposited Data		
Data analysed and analysis code	This paper	https://doi.org/10.6084/m9.figshare.11848152
Software and Algorithms		
R	R Core team	https://www.r-project.org/
ModestR	[33]	http://www.ipez.es/ModestR/
lme4 package	[34]	https://github.com/lme4/lme4/
r2glmm package	[35]	https://www.rdocumentation.org/packages/r2glm m
effects package	[36]	https://www.rdocumentation.org/packages/effects/versions/4.1-3/topics/effects-package
ImerTest package	[37]	https://www.rdocumentation.org/packages/ImerTe st/versions/3.1-1
glm	R Core team	https://www.r-project.org/
Other		
Referenced dataset	[17]	doi.org/10.1038/nclimate1958
GBIF	[18]	https://www.gbif.org/
WoRMS	[38]	http://marinespecies.org/
HADISST	[39]	www.metoffice.gov.uk/hadobs/hadisst/.

Full dataset analysis

	Estimate	Std. Error	z value	P	r²
Model 1: glmer(AbundanceCha	nge ~ Position	+ (1 taxa_gp)	+ Timespan +	Sampling + H	emisphere + (1
DOI_Record), family=binomi	al("logit"))				
(Intercept)	-1.169	0.638	-1.833	0.067	_
Position (in species range)	2.665	0.406	6.57	<0.001	0.088
Timespan (of study)	0.002	0.007	0.347	0.728	0.000
Sampling (type timeseries)	-0.261	0.416	-0.626	0.532	0.001
Sampling (type twopoint)	-1.717	1.121	-1.531	0.126	0.004
Hemisphere	0.59	0.512	1.151	0.250	0.006
Model 2: glm(AbundanceChange	e ~ Position,f	amily=binomial	("logit"))		
(Intercept)	-0.6381	0.1865	-3.421	0.001	-
Position (in species range)	1.8748	0.2858	6.561	<0.001	0.075

Records with statistically significant abundance shifts only

	Estimate	Std. Error	z value	P	r²	
Model 1: glmer(AbundanceCha	nge ~ Positi	on + (1 taxa_g	p) + Timespar	n + Sampling	+ Hemisphere +	(1
DOI_Record), family=binomi	al("logit"))					
(Intercept)	-1.99735	1.190	-1.678	0.093	-	
Position (in species range)	3.70236	0.713	5.194	<0.001	0.153	
Timespan (of study)	0.01215	0.017	0.735	0.462	0.004	
Sampling (type timeseries)	-0.30405	0.804	-0.378	0.705	0.002	
Sampling (type twopoint)	-1.86467	1.424	-1.31	0.190	0.012	
Hemisphere	0.50667	0.998	0.508	0.612	0.003	
Model 2: glm(AbundanceChang	e ~ Position,	,family=binomia	l("logit"), d	lata=dat)		
(Intercept)	-1.1933	0.3193	-3.738	0.000	_	
- ·						
Position (in species range)	2.9493	0.5479	5.383	0.000	0.14	

Multispecies studies only

	Estimate	Std. Error	z value	P	r²
Model 1: glmer(AbundanceCha	nge ~ Position	+ (1 taxa_gp)	+ Timespan +	Sampling +	Hemisphere + (
DOI_Record), family=binomia	al("logit"))				
(Intercept)	-1.101763	0.751	-1.467	0.143	_
Position (in species range)		0.420	5.988	<0.001	0.087
Timespan (of study)	0.001139	0.008	0.142	0.887	0.000
Sampling (type timeseries)	-0.094943	0.471	-0.202	0.840	0.000
Sampling (type twopoint)	-1.863263	1.120	-1.663	0.096	0.006
Hemisphere	0.759877	0.580	1.31	0.190	0.010
Model 2: glm(AbundanceChange	e ~ Position,fa	mily=binomial("	logit"))		
(Intercept)	-0.4646	0.1965	-2.365	0.018	-
Position (in species range)	1.727	0.2985	5.785	0.000	0.650

Spatially-thinned records

	Estimate	Std. Error	z value	P	r²
Model 1: glmer(AbundanceCha	ange ~ Position	+ (1 taxa_gp)	+ Timespan +	Sampling + Her	misphere + (1
DOI_Record), family=binom:	ial("logit"))				
(Intercept)	-1.173461	0.63802	-1.839	6.59E-02	-
Position (in species range)	2.661017	0.405128	6.568	5.09E-11	0.960
Timespan (of study)	0.002592	0.007177	0.361	0.718	0.001
Sampling (type timeseries)	-0.252619	0.41595	-0.607	0.5436	0.001
Sampling (type twopoint)	-1.720151	1.120568	-1.535	0.1248	0.011
Hemisphere	0.585845	0.511921	1.144	0.2525	0.007

Records with r values reported

	Estimate	Std. Err	or df	t	P	r²		
Model 3: lmer(r ~ Position + (1 taxa_gp) + Timespan + Sampling + Hemisphere + (1 DOI_Record)								
(Intercept)	-0.111502	0.588	18.397889	-0.190	0.852	-		
Position (in species range)	0.437045	0.156	61.224134	2.808	0.007	0.062		
Timespan (of study)	-0.002105	0.006	21.001368	-0.336	0.740	0.002		
Sampling (type timeseries)	-0.168088	0.414	18.68575	-0.406	0.689	0.003		
Sampling (type twopoint)	-0.11274	0.650	13.713493	-0.174	0.865	0.001		
Position (in species range)	-0.414449	0.607	17.763703	-0.682	0.504	0.008		
	Estimate	Std. Err	or t	P	r²			
Model 4: lm(r ~ Position)								
(Intercept)	-0.1526	0.1039	-1.468	0.146	_			
Position (in species range)	0.3738	0.1795	2.083	0.041	0.055			

Table S1: Summary of model fixed effects, related to Figure 2.

Generalized Linear Mixed-Effects Model (Model 1) for association between the response variable (direction of the abundance change) and predictor variables and generalised linear model results for the reduced model (Model 2). A linear mixed-effect model was used for r value analysis as the values were continuous (Model 3) and a linear model for the reduced model (Model 4).

Position*Group

	Estimate	Std. Error	z value	P	r²
AbundanceChangeN ~ Position* taxa	a_gp, family	=binomial("logi	t")		
(Intercept)	-0.73505	0.26062	-2.82	0.0048	-
Position (in species range)	1.88364	0.36516	5.158	2.49E-07	0.013
taxa_gp Invertebrates	0.07137	0.66351	0.108	0.9143	0.000
taxa_gp Larval fish	0.0791	0.65053	0.122	0.9032	0.007
taxa_gp Seabirds	-0.96201	0.83925	-1.146	0.2517	0.000
taxa_gp Zooplankton	-2.52858	1.6025	-1.578	0.1146	0.010
Position * taxa_gp Invertebrates	0.04586	1.11113	0.041	0.9671	0.000
Position * taxa_gp Larval fish	11.13908	4.94277	2.254	0.0242	0.221
Position * taxa_gp Seabirds	1.16963	1.48568	0.787	0.4311	0.000
Position * taxa_gp Zooplankton	1.98631	2.19916	0.903	0.3664	0.005

Group-specific models

glm(Abundance Change~ Position, family = binomial("logit"))

	Estimate	Std. Error	z value	P	r²
Zooplankton					
(Intercept)	-3.264	1.581	-2.064	0.039	-
Position (in species range)	3.870	2.169	1.785	0.074	0.316
Seabirds					
(Intercept)	-1.697	0.798	-2.127	0.033	-
Position (in species range)	3.053	1.440	2.120	0.034	0.118
Benthic Invertebrates					
(Intercept)	-0.664	0.610	-1.088	0.277	-
Position (in species range)	1.930	1.049	1.839	0.066	0.052
Fish					
(Intercept)	-0.735	0.261	-2.820	0.005	-
Position (in species range)	1.884	0.365	5.158	<0.001	0.079
Larval bony fish					
(Intercept)	-0.656	0.596	-1.100	0.271	-
Position (in species range)	13.023	4.931	2.641	0.008	0.335

Table S2. Summary of model fixed effects, related to Figure 3.

Generalized linear models for testing for dependence of the response variable (direction of the abundance change) on both the position in range and taxonomic/functional group. The analysis included only the five most well represented groups within the main dataset.