

1 Adaptive foraging behaviour increases vulnerability to climate change

2

3

4 Benoit Gauzens^{1,2,*}, Benjamin Rosenbaum^{1,2}, Gregor Kalinkat³, Thomas Boy^{1,2}, Malte

5 Jochum^{4,5}, Susanne Kortsch⁶, Eoin J. O’Gorman⁷, Ulrich Brose^{1,2}

6

7 ¹ EcoNetLab, German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig,
8 Leipzig, Germany

9 ² Institute of Biodiversity, Friedrich Schiller University Jena, Jena, Germany

10 ³ Department of Ecohydrology, Leibniz Institute of Freshwater Ecology and Inland Fisheries
11 (IGB), Berlin, Germany

12 ⁴ Experimental Interaction Ecology, German Centre for Integrative Biodiversity Research (iDiv)
13 Halle-Jena-Leipzig, Leipzig, Germany

14 ⁵ Leipzig University, Institute of Biology, Leipzig, Germany

15 ⁶ Department of Agricultural Sciences, University of Helsinki, Finland

16 ⁷ School of Life Sciences, University of Essex, Wivenhoe Park, Colchester CO4 3SQ, UK

17 * Corresponding author: benoit.gauzens@idiv.de

18

19

20

21 **Abstract:**

22

23 Adaptative foraging behaviour should promote species coexistence and biodiversity under
24 climate change as consumers are expected to maximise their energy intake, according to
25 principles of optimal foraging theory. We test these assumptions using a unique dataset
26 comprising (1) 22,185 stomach contents of fish species across functional groups and feeding
27 strategies and (2) prey availability in the environment over 12 years. We explore how foraging
28 behavior responds to variance in ecosystem productivity and temperature. Our results show that
29 foraging shifts from trait-dependent prey selectivity to simple density dependence in warmer and
30 more productive environments. Contrary to classical assumptions, we show that this
31 behavioural change leads to lower consumption efficiency as species shift away from their
32 optimal trophic niche. Dynamic food-web modeling demonstrates that this behavioral response
33 to warming could undermine species persistence and biodiversity. By integrating empirical
34 adaptive foraging behavior into dynamic models, our study reveals higher risk profiles for
35 ecosystems under global warming.

36

37 Introduction

38

39 Ecosystems are experiencing abrupt changes in climatic conditions, making it ever more
40 important to predict and understand how they will respond to future changes. Global warming
41 will affect various levels of biological organisation; from physiological processes occurring at the
42 individual level^{1,2} to patterns at macroecological scales^{3,4}. Warming impacts will cascade
43 through these different organisational levels, changing species composition⁵ as well as
44 community and food web structure⁶⁻⁸. By scaling up temperature effects from species
45 physiology to food webs⁹, trophic interactions play a key role in the response of ecosystems to
46 global warming¹⁰.

47 To assess the future of ecological communities, food web models that build on biological
48 processes observed at the level of individual organisms can be used to translate mechanisms
49 and predictions to the ecosystem level. For example, Allometric Trophic Networks¹¹ (ATN)
50 quantify effects of body mass and temperature on the biological rates of consumers and
51 resources to predict species biomass changes over time and across environmental
52 conditions^{11,12}. Thus, ATNs facilitate understanding of how physiological responses to warming
53 translate into species coexistence and biodiversity¹². However, the ability of ATNs to derive
54 sound predictions for large communities under changing environmental conditions has been
55 challenged, stressing the need for more biological realism^{10,15}.

56 Indeed, a strong limitation of these models is that species are characterised by a set of
57 biological rates that respond to temperature, such as metabolic or attack rates¹⁶⁻¹⁸. Therefore,
58 species are limited to physiological response to warming, whereas the behavioural component
59 is largely ignored. However it is well established that species also respond to warming by
60 changing their behaviour^{19,20}, and that this is a key variable in supporting species coexistence²¹⁻
61 ²⁵, which needs to be incorporated into food web models to improve their predictive power.

62 Energetic demands increase with temperature, but species can offset this by adopting various
63 strategies to increase their energy intake. Species can actively forage on more rewarding
64 resources^{27,28}, typically prey that are close to the maximum body mass that consumers can feed
65 on²⁹. Therefore we expect that predators consume larger prey (trait-based selectivity) at higher
66 temperatures, reducing predator-prey body mass ratios (H1). Alternatively, individuals under
67 high energetic stress may accept less rewarding (smaller, but more abundant) prey upon
68 encounter (H2) leading to a lower trait-based selectivity, and a trophic niche driven more by
69 neutral processes (random encounter probability). The two proposed hypotheses would lead to
70 contrasting effects on communities. Trait-based selectivity (H1) may increase the strength of

71 consumer interactions with a limited set of prey, depleting the latter's biomass. Alternatively, if
72 neutral processes are driving selectivity (H2), consumers will mostly forage on abundant
73 species, leading to a stronger control of their biomass, which could prevent competitive
74 exclusion and therefore enhance species coexistence^{25,32}. To test these hypotheses, we
75 compiled a database of 22,185 stomach contents from 6 demersal fish species and analysed
76 the response of these consumers to changes in temperatures and productivity. Subsequently,
77 we addressed the consequences of these empirical relationships by integrating them into a
78 population-dynamical model to predict how species coexistence changes with warming.

79

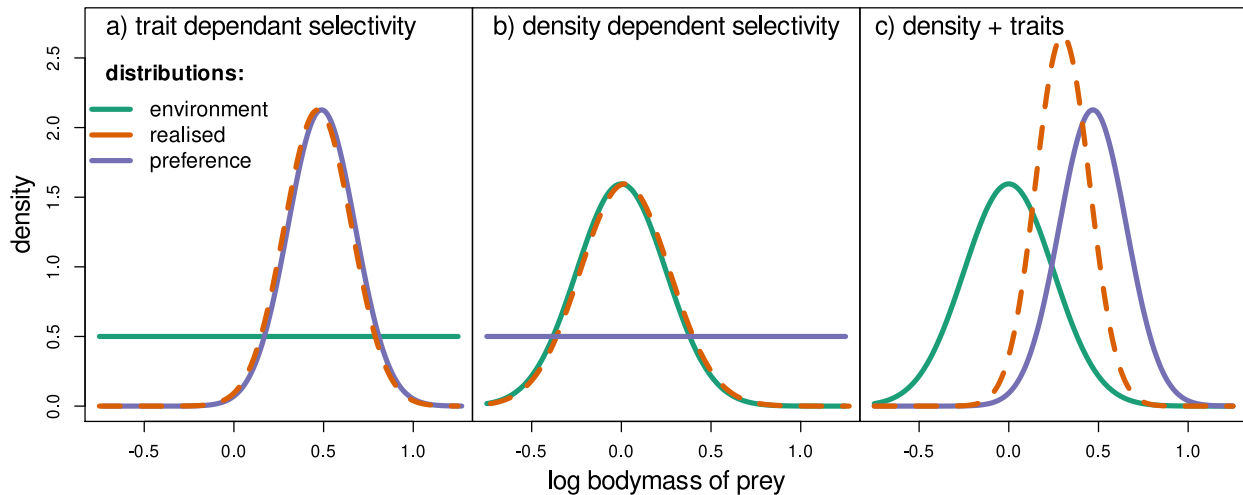
80 **Response of fish to temperature and productivity gradients**

81

82 We used our database to document how consumer foraging behaviour responds to temperature
83 and productivity. The six fish species considered belong to two functional groups differing in
84 body shape and foraging behaviour (flat, sit-and-wait predators versus fusiform, active hunters).
85 We used skewed normal distributions to fit the prey body mass distributions observed in fish
86 stomachs (hereafter called the *realised distribution*) and in their environment (hereafter called
87 the *environmental distribution*) (Fig. 1). The environmental distribution defines what is expected
88 if neutral processes drive fish diets: it represents the expected body mass distribution of prey in
89 fish stomachs if consumption were driven by density-based encounter rates only. However,
90 these two distributions are usually not identical, because consumers actively select prey with
91 specific body masses. We used the ratio of realised and environmental distributions to calculate
92 fish selectivity with respect to these different prey body masses to obtain a *preference*
93 *distribution* (see Fig. 1, Methods). This preference distribution describes consumer selectivity
94 based on traits (i.e. the prey body masses that allow an interaction) and consumer behavioural
95 decisions.

96

97



98

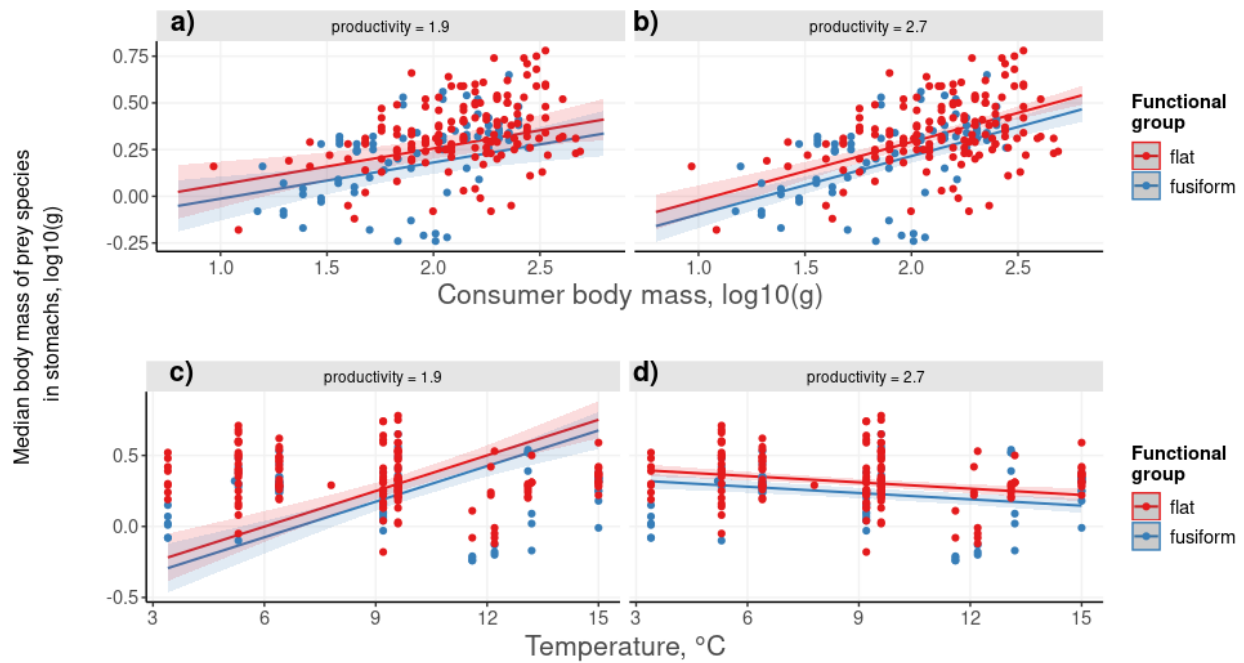
99 Fig. 1: Presentation of the different distributions of fish prey body mass. The environmental distribution
100 (green) represents the distribution of prey body mass in the ecosystem. The realised distribution (dashed
101 red) represents the body mass of the prey in a consumer stomach, and the preference distribution (blue)
102 represents the selectivity of a consumer towards a specific prey body mass. a) All of the log prey body
103 masses are equally represented in the environment so the distribution of prey body masses observed in a
104 consumer's gut represents the body masses on which it actively foraged (its preference distribution)
105 and predation is driven by trait selectivity only (hypothesis 1). b) The body mass distribution of the prey
106 observed in the gut and in the environment are equivalent, so the prey consumed by the predator were
107 entirely driven by encounter probabilities (i.e. a neutral process), implying no active selectivity over
108 specific prey size classes (hypothesis 2). Panels a) and b) represent extreme scenarios while real-world
109 data are more likely to be described by two different distributions, as in c) where the body mass
110 distribution of prey observed in the stomach and in the environment differs, so that the consumer
111 specifically forages on some prey body masses that are represented by the preference distribution. High
112 values in the preference distribution represent body masses that are over-represented in fish stomachs in
113 comparison to what is available in the environment.

114

115

116 We first considered how the body mass distributions in consumer stomachs were changing with
117 predator body mass and foraging strategy, as well as environmental conditions (temperature
118 and productivity) using a linear model to predict the median of the realised distribution.

119 We selected the most parsimonious model based on AIC. In cases of a significant interaction
120 between temperature and productivity, we presented the effect of temperature at two different
121 levels of productivity (which is a continuous variable) that correspond to the two modes of the
122 distribution of environmental productivity (SI II). As expected^{33,34}, we observed that the median
123 of prey body mass increased with predator body mass (Fig. 2a, b, Table 1).



124

125 Fig. 2: Response of the median body mass of the realised prey body mass distribution to predator body
 126 mass (a, b), and temperature (c, d) at different productivity levels for the two fish functional groups. Points
 127 represent non-transformed data across all productivity levels and lines present model predictions. The
 128 shaded areas show the 95% confidence interval on the predicted values. Colours represent the fish
 129 functional groups (flat versus fusiforms).

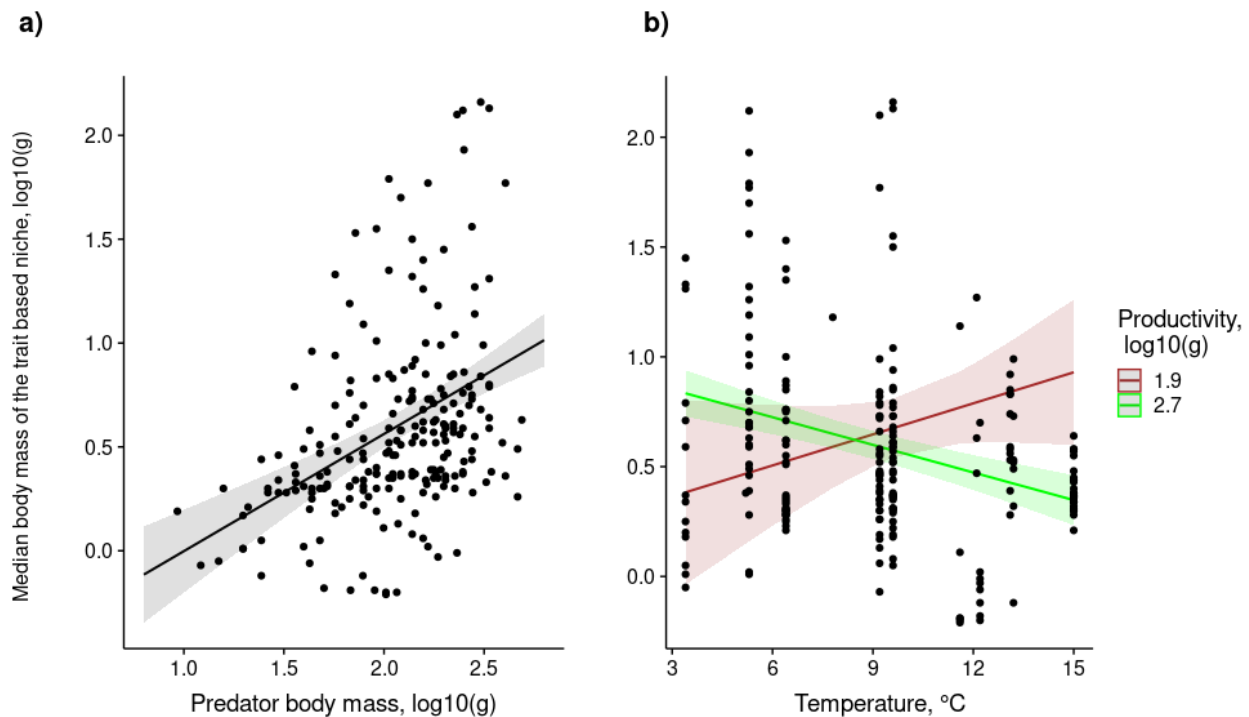
130

131 The effect of temperature depended
 132 on environmental productivity: the
 133 body mass of consumed prey
 134 increased with temperature at low
 135 environmental productivity, but tended
 136 to decrease at higher productivity (Fig
 137 2c, d, Table 1). Interestingly, the
 138 response of prey body mass was
 139 identical for the two different predator
 140 body shapes and foraging strategies.
 141 These effects alone are insufficient to
 142 describe a change in fish behaviour as
 143 the distribution of prey body mass also
 144 changes along environmental

Table 1: response of the realised distribution to predator body mass and environmental gradients

Predictors	median of the realised distribution		
	Estimates	CI	p
(Intercept)	-2.63	-3.68 – -1.57	<0.001
Predator body mass	-0.13	-0.50 – 0.25	0.509
Productivity	0.91	0.51 – 1.31	<0.001
Shape (fusiform)	-0.08	-0.12 – -0.03	0.001
Temperature	0.33	0.25 – 0.41	<0.001
pred. BM:Productivity	0.16	0.01 – 0.30	0.034
Productivity:Temperature	-0.13	-0.16 – -0.10	<0.001
Observations	223		
R ² / R ² adjusted	0.449 / 0.434		

145 gradients (SI II). To disentangle the effect of prey availability (neutral processes) from the fish
146 behavioural response, we estimated the preference distribution that depicts fish selectivity
147 independently of the environmental prey distribution (see Methods). We analysed the response
148 of this fish preference distribution in the same way as for the realised distribution. Our results
149 confirm the importance of species traits for structuring trophic interactions, as larger fish are
150 foraging on larger prey (Fig. 3a). They also emphasize that ecosystem productivity alters the
151 temperature-dependence of fish foraging behaviour with a significant interaction between
152 temperature and productivity (Fig 3b, Table 2). The temperature effect was only significant
153 above a productivity threshold of $10^{2.52}$ (SI III) indicating that fish only adapted their feeding
154 behaviour to temperature by foraging on smaller prey in warmer conditions when resources
155 were plentiful. We did not detect any interaction between fish shape and other covariates,
156 suggesting that the behavioural responses to temperature and productivity are similar for fish
157 species with different body shape and foraging strategies.
158



159
160
161
162
163
164
165
166

Fig. 3: Response of the median prey body mass of the preference distribution to predator body mass, temperature and productivity. Points represent non-transformed data across all productivity levels and lines represent model predictions. The shaded areas show the 95% confidence interval on the predicted values. Grey and green colour represent two different productivity levels at which the temperature effect is represented.

167 The energetic stress that warming imposes on individuals through increased metabolic rates
168 should be mitigated by higher feeding rates at higher prey availability in more productive
169 environments. Thus, because the effects of temperature and productivity should cancel each
170 other out, we expected a stronger adaptive response at low productivity, where consumers must
171 cope with maximum energetic stress. Surprisingly, we did not find a significant effect of
172 temperature on preference for prey sizes in the least productive environments (Fig. 3b, SI III).
173 One explanation for this may relate to the generally low productivity of the Baltic Sea at the
174 period of our study^{35,36}. At very low productivity, fish are experiencing high energetic stress
175 (regardless of temperature) because resource density is low and they cannot afford to miss a
176 prey upon encountering it, even if this prey is far from their preferred body size. Under such
177 stressful conditions, there may be no scope for predators to adapt their feeding behaviour as
178 temperature increases. In more productive environments, feeding behaviour may be less
179 constrained, increasing the adaptive capacity of the fish. Indeed, under such conditions, a cold
180 temperature corresponds to low energetic stress due to a combination of low energetic demand
181 and high resource availability), which allows fish to select prey based on traits. However,
182 warming increases energetic stress because the resource availability is similar whereas the
183 energetic demand rises, forcing fish to engage in non-selective behaviour.

184
185 Therefore, our results support hypothesis 2 that as temperature increases in productive
186 environments, fish become less selective for prey size so as not to miss foraging opportunities,
187 which is consistent with what happens at any temperature when productivity is low. This feeding
188 behaviour, which lowers trait-based selectivity, imposes several disadvantages on consumers.
189 As smaller prey are more abundant, consumers miss out on larger and thus energetically more
190 rewarding resources while handling smaller prey. Indeed, our analyses reveal that consumers
191 miss these larger prey, as we observed a very weak and negative temperature effect on the
192 width of consumer trophic niches (SI IV). This suggests that the increased consumption of
193 smaller prey in warmer environments happens at the cost of missing out on larger prey, which
194 can be critical to satisfying the energetic needs of consumer species³⁷. This observation tends
195 to mitigate our assumption that adaptive behaviour leading to more neutral-driven consumption
196 should increase species coexistence in the face of warming. Indeed, metabolic rates increase
197 with warming faster than feeding rates, leading to the extinction of top predators due to
198 starvation^{31,38,39}. This starvation effect explained by physiological process can cumulate with our
199 observed behavioural response: consuming outside of the most efficient predator-prey body
200 mass ratio is, in general, associated with a lower energy flux through food webs, which may limit

201 the coexistence of consumer species^{37,40}. The combination of direct and indirect effects of
202 warming could increase the likelihood of extinction of top predators in food webs, which are
203 usually considered key species for the maintenance of biodiversity and ecosystem
204 functionality⁴¹.

205

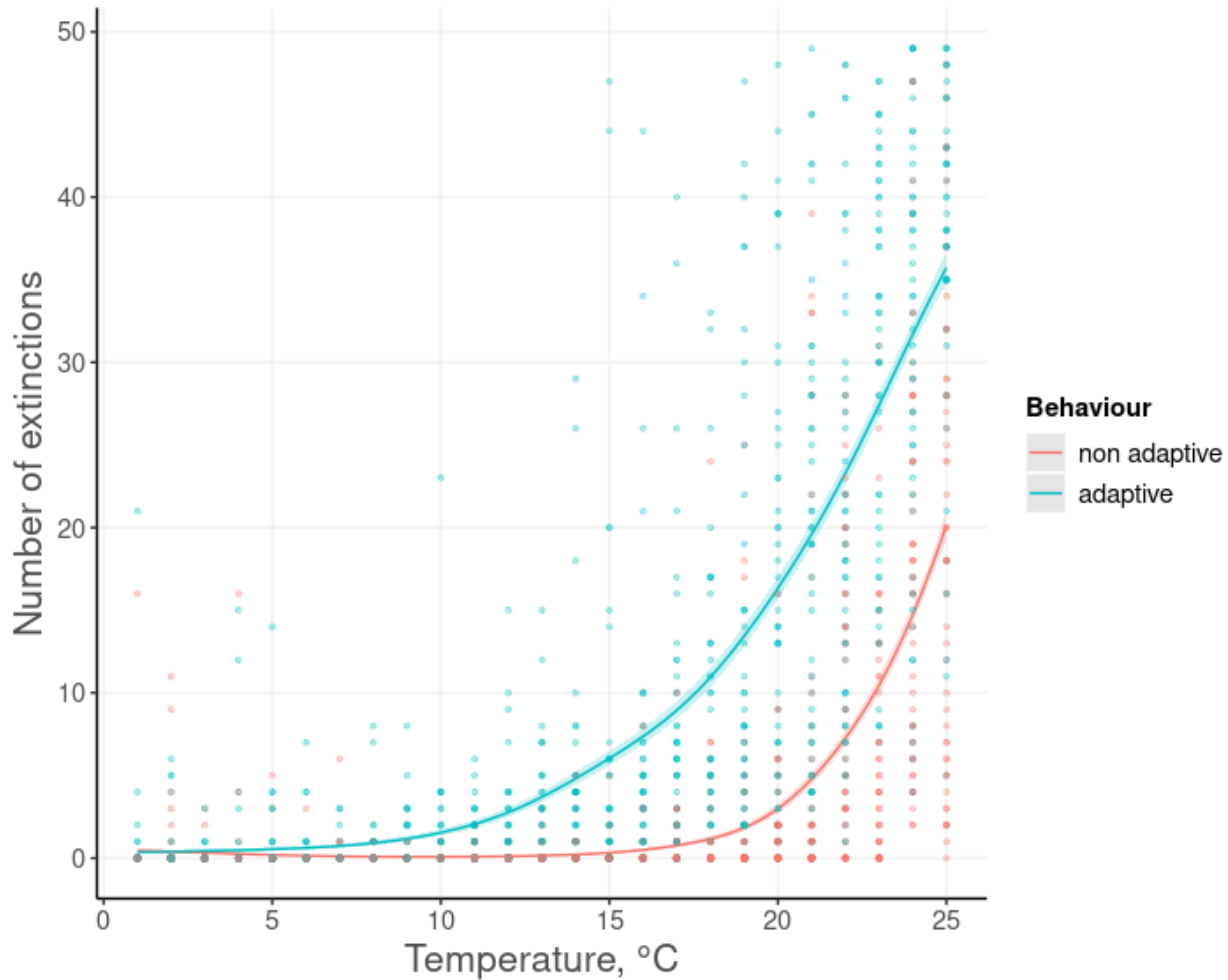
206 **Consequences for species coexistence under global warming**

207

208 Adaptive foraging in response to varying local conditions is often considered to foster species
209 coexistence^{25,26,42}. The general assumption behind this conclusion is that consumer species will
210 adapt their foraging strategies in order to maximise their energetic gains⁴³. However, our results,
211 based on an allometric framework, suggest that consumers tend to depart from this optimal
212 behaviour under stressful conditions. We explored the consequences of this behaviour using a
213 population dynamic model that predicts the temporal dynamics and coexistence of species in
214 food webs. The model was parameterized with species body masses and temperature (see
215 Methods). We ran two versions of this model: one including adaptation of species diets to local
216 temperature and productivity conditions as informed by our empirical results, and one without
217 this adaptation, corresponding to the classical modelling approach⁴⁴. We simulated the
218 dynamics for synthetic food webs of 50 species (30 consumers and 20 basal species) over a
219 temperature gradient spanning from 1°C to 25°C to predict the number of extinctions at different
220 temperatures. Overall, we observed that models incorporating adaptive foraging were more
221 sensitive to warming (Fig. 4), as for models without behavioural adaptation the proportion of
222 extinct species remained low over a larger temperature gradient. These results were not
223 affected by the choice of specific values for ecosystem nutrient availability or the functional
224 response type that are free parameters of our model (SI V)

225

226



227

228 Fig. 4: Number of species extinctions predicted by the model at different temperatures. The blue line
229 represents the model output with adaptation of species' diet to local temperature and productivity
230 conditions was considered, the red line shows extinctions without allowing for this adaptation. The shaded
231 areas show the 95% confidence interval on the predicted values. Predictions were estimated using a
232 GAM (REML method) with a binomial link function.

233

234 The effects of warming on the trait structure of communities⁸ and the distribution of trophic
235 interactions⁷ are well documented, but a framework for integrating changes in feeding
236 behaviour with a general modelling approach has been lacking. Our results stress the
237 importance of accounting for foraging behaviour to better understand and predict community
238 responses to climate change and challenge previous conclusions on this topic. Indeed, the
239 discrepancies between the models with and without adaptive foraging suggest that the classical
240 approach, which only accounts for changes in species physiology^{10,12}, may have overlooked a
241 significant portion of species responses to warming. Importantly, our results show that, contrary

242 to common expectation, behavioural adaptations in response to climatic stress reduce the
243 likelihood of species coexistence and community biodiversity.

244

245 **Future directions**

246

247 The similarity in responses between the two feeding strategies (sit-and-wait and active foraging)
248 of our consumer species indicates some generality of our results, but it is now important to
249 further generalize our results across a wider range of species and ecosystem types. For
250 instance, metabolic type has an important effect on the response of species to temperature⁴⁵
251 and endotherms could respond differently to ectotherms such as fish.

252 Generally, food web models incorporating foraging behaviour are based on optimal foraging
253 theory and thus miss a data-driven description of how consumers' diet selectivity changes in a
254 natural context. To address this, we developed a trait-based framework to document the
255 response of foraging behaviour to temperature that can be incorporated into predictive food web
256 models and allowing us to derive predictions on species coexistence. Our approach can be
257 generalised to other ecological variables that affect food webs and foraging behaviour, such as
258 fear of predators³⁰ or habitat complexity⁴⁶ for instance. Finally, the effects documented here
259 come from data sampled at rather low temperatures and levels of productivity. Therefore, it is
260 crucial to extend our regression models to more productive and warm ecosystems. For
261 instance, one can argue that very high levels of productivity would balance the energetic stress
262 related to temperature increase, limiting fish adaptive response to warming in eutrophic
263 environments.

264

265 **Conclusion**

266

267 It is generally assumed that consumers respond to environmental conditions by making optimal
268 choices maximising their energetic income^{26,47,48}. This assumption was used to derive several
269 predictions in ecology about community structure and species coexistence. For instance, it is
270 often considered as a solution to May's paradox⁴⁹ based on the discrepancy between the
271 prediction of a mathematical model posing that complex communities should not persist in
272 nature and empirical observations of ecosystem complexity. It is therefore usually assumed that
273 species' behaviour is a strong driver of community organisation and supports species
274 coexistence. We challenge this optimistic view of nature by emphasizing that under stressful
275 conditions, when resources are scarce and species energetic needs high - for instance when

276 they face energetic stress caused by temperature increase - consumer species tend to depart
277 from what would be their optimal behaviour under low-stress conditions. Therefore, the
278 ecological conclusions built into the assumptions that adaptive behaviour favours coexistence
279 do not necessarily hold in the context of global warming. We tested the consequences of our
280 observations by integrating this behavioural response in a mechanistic model. We show that the
281 number of species extinctions in response to an increase in temperature is higher than what is
282 observed without. This means that the consequences of global warming for species coexistence
283 might be more severe than predicted by classical ecological models. Our findings also challenge
284 the general paradigm that adaptive foraging should mitigate the consequences of global
285 warming for natural ecosystems. Instead, the drastic consequences of climate change indicated
286 by our results call for a general data-driven theory-approach to forecast of biodiversity and
287 functioning in future ecosystems.

288

289 **Acknowledgements**

290

291 We are profoundly grateful that Wolf E. Arntz collected and provided the valuable data set from
292 his early work in Kiel Bay that we used in this study. We are also thankful to Astrid Jarre who
293 digitised the stomach content data, Ute Jacob for her help in the early phase of this project and
294 Carlos Melian for his friendly review of the manuscript. BG, UB, BR, TB, MJ gratefully
295 acknowledge the support of iDiv funded by the German Research Foundation (DFG–FZT 118,
296 202548816). GK acknowledges funding from the German Academic Exchange Service (DAAD,
297 57070483). MJ acknowledges funding by the European Research Council (ERC) under the
298 European Union’s Horizon 2020 research and innovation programme (grant agreement no.
299 677232).

300

301 **References**

302

- 303 1. Dell, A. I., Pawar, S. & Savage, V. M. Systematic variation in the temperature
304 dependence of physiological and ecological traits. *Proc. Natl. Acad. Sci. U. S. A.* **108**,
305 10591–10596 (2011).
- 306 2. Seebacher, F., White, C. R. & Franklin, C. E. Physiological plasticity increases resilience
307 of ectothermic animals to climate change. *Nat. Clim. Chang.* **5**, 61–66 (2015).

- 308 3. Yvon-Durocher, G., Jones, J. I., Trimmer, M., Woodward, G. & Montoya, J. M. Warming
309 alters the metabolic balance of ecosystems. *Philos. Trans. R. Soc. B Biol. Sci.* **365**,
310 2117–2126 (2010).
- 311 4. Free, C. M. *et al.* Impacts of historical warming on marine fisheries production. *Science*
312 (80-). **363**, 979–983 (2019).
- 313 5. Lenoir, J. *et al.* Species better track climate warming in the oceans than on land. *Nat.*
314 *Ecol. Evol.* **4**, 1044–1059 (2020).
- 315 6. Weinbach, A., Allhoff, K., Thebault, E., Massol, F. & Loeuille, N. Selective effects of
316 temperature on body mass depend on trophic interactions and network position. *bioRxiv*
317 233742 (2017) doi:10.1101/233742.
- 318 7. Gibert, J. P. Temperature directly and indirectly influences food web structure. *Sci. Rep.*
319 **9**, 1–8 (2019).
- 320 8. O’Gorman, E. J. *et al.* A simple model predicts how warming simplifies wild food webs.
321 *Nature Climate Change* vol. 9 611–616 (2019).
- 322 9. Petchey, O. L., Brose, U. & Rall, B. C. Predicting the effects of temperature on food web
323 connectance. *Philos. Trans. R. Soc. B Biol. Sci.* **365**, 2081–2091 (2010).
- 324 10. Gauzens, B., Rall, B. C., Mendonça, V., Vinagre, C. & Brose, U. Biodiversity of intertidal
325 food webs in response to warming across latitudes. *Nat. Clim. Chang.* **10**, 264–269
326 (2020).
- 327 11. Martinez, N. D. Allometric Trophic Networks From Individuals to Socio-Ecosystems:
328 Consumer–Resource Theory of the Ecological Elephant in the Room. *Frontiers in*
329 *Ecology and Evolution* vol. 8 92 (2020).
- 330 12. Binzer, A., Guill, C., Rall, B. C. & Brose, U. Interactive effects of warming, eutrophication
331 and size structure: Impacts on biodiversity and food-web structure. *Glob. Chang. Biol.* **22**,
332 220–227 (2016).
- 333 13. Boit, A., Martinez, N. D., Williams, R. J. & Gaedke, U. Mechanistic theory and modelling
334 of complex food-web dynamics in Lake Constance. *Ecol. Lett.* **15**, 594–602 (2012).
- 335 14. Curtsdotter, A. *et al.* Ecosystem function in predator–prey food webs—confronting
336 dynamic models with empirical data. *J. Anim. Ecol.* **88**, 196–210 (2019).
- 337 15. Sauve, A. M. C. & Barraquand, F. From winter to summer and back: Lessons from the
338 parameterization of a seasonal food web model for the Białowieża forest. *J. Anim. Ecol.*
339 **89**, 1628–1644 (2020).
- 340 16. Rall, B. C. *et al.* Universal temperature and body-mass scaling of feeding rates. *Philos.*
341 *Trans. R. Soc. B Biol. Sci.* **367**, 2923–2934 (2012).

- 342 17. Gilbert, B. *et al.* A bioenergetic framework for the temperature dependence of trophic
343 interactions. *Ecol. Lett.* **17**, 902–914 (2014).
- 344 18. Bideault, A. *et al.* Thermal mismatches in biological rates determine trophic control and
345 biomass distribution under warming. *Glob. Chang. Biol.* **27**, 257–269 (2021).
- 346 19. Abram, P. K., Boivin, G., Moiroux, J. & Brodeur, J. Behavioural effects of temperature on
347 ectothermic animals: unifying thermal physiology and behavioural plasticity. *Biol. Rev.* **92**,
348 1859–1876 (2017).
- 349 20. Sentis, A., Gémard, C., Jaugeon, B. & Boukal, D. S. Predator diversity and environmental
350 change modify the strengths of trophic and nontrophic interactions. *Glob. Chang. Biol.* **23**,
351 2629–2640 (2017).
- 352 21. Abrams, P. A. Dynamics and Interactions in Food Webs with Adaptive Foragers. in *Food*
353 *Webs* 113–121 (Springer US, 1996). doi:10.1007/978-1-4615-7007-3_11.
- 354 22. Abrams, P. & Matsuda, H. Effects of adaptive predatory and anti-predator behaviour in a
355 two-prey-one-predator system. *Evol. Ecol.* **7**, 312–326 (1993).
- 356 23. Valdovinos, F., Ramos-Jiliberto, R., Garay-Narva´ez, L., Pasquinell, U. & Dunne, J. A.
357 Consequences of adaptive behaviour for the structure and dynamics of food webs. *Ecol.*
358 *Lett.* **13**, 1546–1559 (2010).
- 359 24. Kondoh, M. Foraging adaptation and the relationship between food-web complexity and
360 stability. *Science (80-.)*. **299**, 1388–1391 (2003).
- 361 25. Kondoh, M. Does foraging adaptation create the positive complexity-stability relationship
362 in realistic food-web structure? *J. Theor. Biol.* **238**, 646–51 (2006).
- 363 26. Kondoh, M. Foraging adaptation and the relationship between food-web complexity and
364 stability. *Science (80-.)*. **299**, 1388–91 (2003).
- 365 27. Lemoine, N. P., Drews, W. A., Burkepile, D. E. & Parker, J. D. Increased temperature
366 alters feeding behavior of a generalist herbivore. *Oikos* **122**, 1669–1678 (2013).
- 367 28. Sentis, A., Hemptinne, J. L. & Brodeur, J. Towards a mechanistic understanding of
368 temperature and enrichment effects on species interaction strength, omnivory and food-
369 web structure. *Ecol. Lett.* **17**, 785–793 (2014).
- 370 29. Portalier, S. M. J., Fussmann, G. F., Loreau, M. & Cherif, M. The mechanics of predator–
371 prey interactions: First principles of physics predict predator–prey size ratios. *Funct. Ecol.*
372 **33**, 323–334 (2019).
- 373 30. Ho, H., Tylilanakis, J. M., Zheng, J. X. & Pawar, S. Predation risk influences food-web
374 structure by constraining species diet choice. *Ecol. Lett.* **22**, 1734–1745 (2019).
- 375 31. Binzer, A., Guill, C., Brose, U. & Rall, B. C. The dynamics of food chains under climate

- 376 change and nutrient enrichment. *Philos. Trans. R. Soc. B Biol. Sci.* **367**, 2935–2944
377 (2012).
- 378 32. Gauzens, B., Legendre, S., Lazzaro, X. & Lacroix, G. Intermediate predation pressure
379 leads to maximal complexity in food webs. *Oikos* **125**, 595–603 (2016).
- 380 33. Tsai, C.-H., Hsieh, C. & Nakazawa, T. Predator-prey mass ratio revisited: Does
381 preference of relative prey body size depend on individual predator size? *Funct. Ecol.*
382 (2016) doi:10.1111/1365-2435.12680.
- 383 34. Brose, U. *et al.* Predator traits determine food-web architecture across ecosystems. *Nat.*
384 *Ecol. Evol.* **3**, 919–927 (2019).
- 385 35. Elmgren, R. & Hill, C. Ecosystem function at low biodiversity – the Baltic example. in
386 *Marine Biodiversity* 319–336 (Cambridge University Press, 2010).
387 doi:10.1017/cbo9780511752360.015.
- 388 36. Elmgren, R. Man’s impact on the ecosystem of the Baltic Sea: Energy flows today and at
389 the turn of the century. *Ambio* **18**, 326–332 (1989).
- 390 37. Brose, U. Body-mass constraints on foraging behaviour determine population and food-
391 web dynamics. *Funct. Ecol.* **24**, 28–34 (2010).
- 392 38. Petchey, O. L., McPhearson, P. T., Casey, T. M. & Morin, P. J. Environmental warming
393 alters food-web structure and ecosystem function. *Nature* **402**, 69–72 (1999).
- 394 39. Vucic-Pestic, O., Ehnes, R. B., Rall, B. C. & Brose, U. Warming up the system: Higher
395 predator feeding rates but lower energetic efficiencies. *Glob. Chang. Biol.* **17**, 1301–1310
396 (2011).
- 397 40. Guzman, L. M. & Srivastava, D. S. Prey body mass and richness underlie the persistence
398 of a top predator. *Proc. R. Soc. B Biol. Sci.* **286**, (2019).
- 399 41. Birkeland, C. & Dayton, P. K. The importance in fishery management of leaving the big
400 ones. *Trends in Ecology and Evolution* vol. 20 356–358 (2005).
- 401 42. Stump, S. M. & Chesson, P. How optimally foraging predators promote prey coexistence
402 in a variable environment. *Theor. Popul. Biol.* **114**, 40–58 (2017).
- 403 43. Pyke, G. H., Pulliam, H. R. & Charnov, E. L. Optimal Foraging: A Selective Review of
404 Theory and Tests. *Q. Rev. Biol.* **52**, 137–154 (1977).
- 405 44. Schneider, F. D., Brose, U., Rall, B. C. & Guill, C. Animal diversity and ecosystem
406 functioning in dynamic food webs. *Nat. Commun.* **7**, 1–8 (2016).
- 407 45. Pinsky, M. L., Eikeset, A. M., McCauley, D. J., Payne, J. L. & Sunday, J. M. Greater
408 vulnerability to warming of marine versus terrestrial ectotherms. *Nature* **569**, 108–111
409 (2019).

- 410 46. Jinks, K. I. *et al.* Habitat complexity influences the structure of food webs in Great Barrier
411 Reef seagrass meadows. *Ecosphere* **10**, e02928 (2019).
- 412 47. Beckerman, A. P., Petchey, O. L. & Warren, P. H. Foraging biology predicts food web
413 complexity. *Proc. Natl. Acad. Sci. U. S. A.* **103**, 13745–9 (2006).
- 414 48. Petchey, O. L., Beckerman, A. P., Riede, J. O. & Warren, P. H. Size, foraging, and food
415 web structure. *Proc. Natl. Acad. Sci. U. S. A.* **105**, 4191–4196 (2008).
- 416 49. May, R. M. Qualitative Stability in Model Ecosystems. *Ecology* **54**, 638–641 (1973).
- 417 50. Russo, T., Costa, C. & Cataudella, S. Correspondence between shape and feeding habit
418 changes throughout ontogeny of gilthead sea bream *Sparus aurata* L., 1758. *J. Fish Biol.*
419 **71**, 629–656 (2007).
- 420 51. Arntz, W. E. Die Nahrung juveniler Dorsche (*Gadus morhua* L.) in der Kieler Bucht. in
421 *Berichte der Deutschen wissenschaftlichen Kommission für Meeresforschung* 129–183
422 (1974).
- 423 52. Lie, U. & Pamatmat, M. M. digging characteristics and sampling efficiency of the 0.1 m²
424 van veen grab. *Limnol. Oceanogr.* **10**, 379–384 (1965).
- 425 53. Gröger, J. & Rumohr, H. Modelling and forecasting long-term dynamics of Western Baltic
426 macrobenthic fauna in relation to climate signals and environmental change. *J. Sea Res.*
427 **55**, 266–277 (2006).
- 428 54. Stan Development Team. RStan: the R interface to Stan. (2020).
- 429 55. Azzalini, A. The R package sn: The Skew-Normal and Related Distributions such as the
430 Skew-t and the SUN (version 2.0.0). (2021).
- 431 56. Jobling, M. Mythical models of gastric emptying and implications for food consumption
432 studies. *Environ. Biol. Fishes* **16**, 35–50 (1986).
- 433 57. Yodzis, P. & Innes, S. Body Size and Consumer-Resource Dynamics. *Am. Nat.* **139**,
434 1151–1175 (1992).
- 435 58. Lang, B., Ehnes, R. B., Brose, U. & Rall, B. C. Temperature and consumer type
436 dependencies of energy flows in natural communities. *Oikos* **126**, 1717–1725 (2017).
- 437 59. Hirt, M. R., Lauermaun, T., Brose, U., Noldus, L. P. J. J. & Dell, A. I. The little things that
438 run: a general scaling of invertebrate exploratory speed with body mass. *Ecology* **98**,
439 2751–2757 (2017).
- 440 60. Delmas, E., Brose, U., Gravel, D., Stouffer, D. B. & Poisot, T. Simulations of biomass
441 dynamics in community food webs. *Methods Ecol. Evol.* **8**, 881–886 (2017).
- 442
- 443

444 **Supplementary information I Methods**

445

446 **The Kiel Bay database**

447

448 The Kiel Bay is located in the Baltic Sea, which is a marginal sea connected to the North
449 Atlantic and considered the largest brackish sea in the world. It is a rather low productivity
450 ecosystem with low biodiversity due to its glacial history and the strong salinity gradients that
451 only few species can tolerate^{35,36}. The core of the Kiel Bay database comprises detailed diet
452 information based on stomach contents from 22185 fish individuals of six species from the Kiel
453 Bay. These species were classified into two functional groups based on their body shape and
454 habitat use: fusiform and benthopelagic species (*Gadus morhua*, *Merlangius merlangius*) versus
455 flat and demersal species (*Limanda limanda*, *Pleuronectes platessa*, *Platichthys flesus*, and
456 *Hippoglossoides platessoides*). This shape characteristic also corresponds to specific foraging
457 behaviour⁵⁰.

458 The fish individuals were sampled using systematic and standardised bottom trawls. The trawls
459 were carried out year-round between 1968 and 1978. The body lengths of fish were measured
460 and rounded to the nearest integer (in cm). Species-specific regressions were used to estimate
461 fish body masses. Stomach contents were identified to the highest taxonomic resolution
462 possible and wet mass determined when possible. Hence, the database includes body size data
463 for all fish (i.e. predators) but also for prey items from the stomach contents⁵¹. In addition, we
464 were able to add independently-sampled abundance and body mass information on the benthic
465 invertebrate (i.e. prey) fauna to the database. These data on prey abundances and body
466 masses were sampled independently at the trawling locations using classical 0.1 m² van Veen
467 grabs⁵², see⁵³ for detailed procedure. We have enriched the database with climatic (i.e.
468 temperature) and oceanographic (i.e. salinity) data and geographical information on the
469 distances between the sampling (trawling) sites. So far, the stomach content data have been
470 published only partially and in German language⁵¹ while parts of the invertebrate abundance
471 data were treated and published separately⁵³. The food web mainly consists of six demersal fish
472 species and more than a dozen benthic invertebrate species from different groups (see Table SI
473 VI 3).

474

475 **Filtering data**

476

477 To make comparisons between the distributions of prey observed in fish stomachs and the ones
478 observed in the environment, we only used a subset of the database for which we were able to
479 (i) associate information about a fish to information about its environment and (ii) have a body
480 mass estimate of prey found in the stomach. We considered this association between fish and
481 environment possible, when they were sampled in the same area and within less than 31 days.
482 This first filter reduced the number of fish used in our analysis to 2,487.
483 On this subset, we considered a unique statistical individual (hereafter called statistical fish) all
484 individuals from the same functional group, occurring at the same place, on the same date with
485 the same body mass. This choice is led by the allometric approach used in our analysis, where
486 all individuals from the same species and with the same body mass are considered identical.
487 This aggregation increases the quality of the estimation of the prey body mass distribution in
488 stomachs at the cost of a lower statistical power for the analyses done on the shape of these
489 distributions. For instance, with a high aggregation level, fewer data points are available to
490 consider the effect of temperature on the average body mass of prey. This approach is therefore
491 conservative as it reduces the probability of type 1 error. Lastly, we found that few fishes were
492 mostly feeding on species that were not detected in the environment, suggesting that the
493 information on the environment was not a good descriptor of available resources. When less
494 than 90% of the prey biomass found in guts was explained by what was found in the
495 environment, the fish were discarded (26 cases) Finally, we obtained a final dataset of 290
496 statistical fish. For our statistical analysis we used fish shape as a covariate instead of fish
497 species. As some species were specific to some temperature or body mass gradients, the
498 species-specific slopes obtained would be meaningless. This question only holds for the
499 analysis about the fish stomach contents. For the analysis of preferences, fish shape or fish
500 species covariate were anyway removed by our AIC criterion.
501 Different factors affect prey retention time in consumers' guts. Temperature is certainly essential
502 but we assume that its impact was the same for all consumers introducing a constant bias with
503 no effect on the trends we observed. However, a more species-specific factor relating to species
504 morphology, like the presence of shells or skeletons, could impact our results. We thus
505 compared two sets of results, one for which we incorporated in the model a lower detection
506 probability for species with hard bodies (presented here), and one for which we did not (SI VI).
507 Overall, the trends and effects observed when including this correction were similar to those
508 observed without correction, thus suggesting an absence of systematic biases.
509
510

511 Fitting of gut content and environmental distributions

512

513 We used a Bayesian approach to fit realised and environmental distributions. For the
514 environment distributions, we fitted skew normal distributions to the observed body masses y ,
515 with environment ID as a random effect. A skew normal distribution is defined by parameters for
516 location ξ , scale ω and shape α . Its probability density function reads

$$517 \quad p(y|\xi, \omega, \alpha) = \frac{1}{\omega\sqrt{2\pi}} \exp\left(\frac{-(y - \xi)^2}{2\omega^2}\right) \left(1 + \operatorname{erf}\left(\alpha \frac{y - \xi}{\omega\sqrt{2}}\right)\right)$$

518 where erf is the Gaussian error function^{54,55}. For $\alpha=0$, this reduces to the non-skewed normal
519 distribution with mean $\mu=\xi$ and standard deviation $\sigma=\omega$. For $\alpha>0$ or $\alpha<0$, the distribution is
520 positively or negatively skewed, where skew $\gamma(\alpha)$, standard deviation $\sigma(\omega, \alpha)$ and mean $\mu(\xi, \omega, \alpha)$
521 are given as functions of location, scale and shape parameters⁵⁵.

522 The statistical model then is defined by an observed body mass y of a prey individual i in
523 environment $ID(i)$ being distributed as

$$524 \quad y_{i,ID} \text{ skewnormal}(\xi_{ID}, \omega_{ID}, \alpha_{ID})$$

525 ($i=1, \dots, N, ID=1, \dots, M$). Using a hierarchical / partial pooling approach, we assume the individual
526 parameters have a joint multivariate normal distribution

$$527 \quad (\xi_{ID}, \omega_{ID}, \alpha_{ID}) \text{ multivariatenormal}((\xi, \omega, \alpha), \Sigma)$$

528 ($ID=1, \dots, M$). The joint mean parameters ξ, ω, α and the 3x3 covariance matrix Σ are estimated
529 during the model fitting approach. We used weakly informative priors for all model parameters.
530 Samples from the posterior distribution were drawn using Hamiltonian Monte Carlo in Stan⁵⁴
531 and posterior medians were used as point estimates of $(\xi_{ID}, \omega_{ID}, \alpha_{ID})$ for the subsequent
532 analyses. The realised distributions were fitted analogously, using predator identity as a random
533 effect. We however included here a correction factor to consider that the probability of detection
534 of prey in guts relates to their body characteristic⁵⁶ (presence or absence of hard body parts like
535 shells or skeleton). We assumed that prey with hard body parts are more likely to be detected in
536 comparison to species composed of soft tissues only because of higher digestion time and
537 corrected their biomass by multiplying it by 0.8. The results found without this correction were
538 similar to the ones observed without (SI VI).

539

540 Determining allometric species' preferences

541

542 The preference distributions of each statistical fish were estimated as the departure of
543 the realised niche from the environmental distribution. We removed the effect of species
544 environmental availability from the realised to define the preference distribution as:

$$545 \quad P = \frac{R}{E},$$

546 where P , R and E represent the preference, realised and environmental distributions,
547 respectively. By doing so, we assumed that a feeding event is defined by two independent
548 probabilities: the probability for a consumer to encounter a prey (defined by the R distribution)
549 and of the probability for a consumer to consume the prey when encountered (given by the
550 preference distribution). To assess changes in the distributions and how they depart from each
551 other, we used variations in the point estimates (median and standard deviation). This limited
552 the amount of information used in our study. Quantifying the neutral versus trait-based
553 processes would benefit from the comparison between the environmental and realised
554 distributions using metrics like the Kullback-Leibler divergence. With such an approach, one
555 could argue that the more divergent the distributions are, the more predation events are driven
556 by traits. However, this would be limited by the impossibility of disentangling the part of the
557 divergences explained by changes in the environmental distribution and what relates to a
558 change in fish behaviour. However, we believe that a more controlled approach in micro- or
559 mesocosms where the body mass distribution of prey species available could be standardised
560 could elegantly solve this issue.

561

562 **Dynamic model**

563

564 To simulate the population dynamics, we used a previously published model⁴⁴, based on the
565 Yodzis and Innes framework⁵⁷. The growth of consumer species B_i is determined by the
566 balance between its energetic income (predation) and its energetic losses (predation
567 metabolism)

568

$$569 \quad \frac{dB_i}{dt} = e_p B_i \sum_j F_{ij} + e_a B_i \sum_j F_{ij} - \sum_j B_i F_{ji} - x_i B_i,$$

570 where $e_p = 0.545$ and $e_a = 0.906$ represent the assimilation efficiency of a consumer foraging on
571 plants and animals, respectively⁵⁸. x_i defines the metabolic rate of species i , which scales
572 allometrically with body mass:

$$573 \quad x_i = x_0 m_i^{-0.25} e^{E x \frac{T_0 - T}{k T_0 T}},$$

574 where $x_0 = 0.314$ is the scaling constant ⁴⁴, $E_x = -0.69$ is the activation energy of metabolic rate
 575 (Binzer et al. 2015), k the Boltzmann constant, $T_0 = 293.15$ the reference temperature in Kelvin
 576 and T the temperature at which the simulation is performed. The trophic interactions are
 577 determined using a functional response F_{ij} that describes the feeding rate of consumer i over
 578 resource j :

$$579 \quad F_{ij} = \frac{\omega_{ij} b_{ij} B_j^{1+q}}{1 + c B_i + \omega_{ij} \sum_k h_{ij} b_{ik} B_k^{1+q}} \cdot \frac{1}{m_x}.$$

580
 581 b_{ij} represent the species-specific capture and is determined by predator and prey body masses:

$$582 \quad b_{ij} = P_{ij} L_{xz}.$$

583 It corresponds to the product of encounter probabilities P_{ij} by the probability that an encounter
 584 leads to a realised predation event L_{ij} . Both quantities are determined by species body masses.
 585 We assume that encounter probability is more likely for species with higher movement speeds
 586 of both consumer and resource species:

$$587 \quad P_{ij} = p_0 m_i^{\beta_i} m_j^{\beta_j} e^{E_p \frac{T_0 - T}{k T_0 T}}.$$

588 Since movement speed scales allometrically and based on feeding type ⁵⁹, we drew β_x and β_z
 589 from according normal distributions (carnivore: $\mu_\beta = 0.42$, $\sigma_\beta = 0.05$, omnivore: $\mu_\beta = 0.19$, $\sigma_\beta =$
 590 0.04 , herbivore: $\mu_\beta = 0.19$, $\sigma_\beta = 0.04$, primary producer: $\mu_\beta = 0$, $\sigma_\beta = 0$). Activation energy E_p is
 591 equal to -0.38 (Binzer et al. 2015). L_{ij} is assumed to follow a Ricker curve (Schneider et al.
 592 2016), defined as:

$$593 \quad L_{xz} = \left(\frac{m_x}{m_z R_{opt}} e^{1 - \frac{m_x}{m_z R_{opt}}} \right)^Y,$$

594 where the optimal consumer-resource body mass ratio $R_{opt} = 47.9$ was calculated from the
 595 observed realised interactions in our dataset. We used a threshold $L_{ij} < 0.01$ under which values
 596 were set to 0, assuming that too small or too large prey are not considered by consumers. The
 597 handling time h_{ij} of i on j is defined as:

$$598 \quad h_{ij} = h_0 m_i^{\eta_i} m_j^{\eta_j} e^{E_h \frac{T_0 - T}{k T_0 T}},$$

599 where the scaling constant h_0 was set to 0.4 and the allometric coefficients for η_i and η_j where
 600 drawn from a normal distribution with mean and standard deviation of -0.48 and 0.03 for η_i and
 601 of -0.66 and 0.02 for η_j . E_h is equal to 0.26. The term w_{ij} informs on species selectivity⁶⁰. For the
 602 models without behavioural expectations we used the classical parametrisation and defined it
 603 for every j as 1 over the number of prey of consumer i . When adaptive behaviour was included

604 in the model, the value was determined by the predictions of the skewed normal distribution we
605 fitted on our dataset. These were informed by the consumer and resource body masses, at
606 given levels of productivity and temperature. To maintain the comparability with the model
607 without adaptive behaviour, the w_{ij} values were normalised to 1 for each consumer. As for our
608 experimental data, productivity was defined as the total biomass of prey available for each
609 consumer. As this value can be highly variable during the simulations, especially in the transient
610 dynamics, we rescaled this value between 0 and 4 to maintain it to a scale that is similar to the
611 one from our dataset that we used to inform the skew normal distributions

612 The biomass dynamic of the basal species i is defined as:

$$613 \frac{dB_i}{dt} = r_i G_i B_i - \sum_j B_j F_{ji} - x_i B_i,$$

614 where $r_i = m_i^{-0.25}$ defines the species growth rate. G_i is the species-specific growth factor,
615 determined by the concentration of two nutrients N_1 and N_2 :

$$616 G_i = \min\left(\frac{N_1}{K_{i1} + N_1}, \frac{N_2}{K_{i2} + N_2}\right),$$

617 Where $K_{i\ell}$ determines the half saturation density of plant i nutrient uptake rate. It is determined
618 randomly from a uniform distribution in $[0.1, 0.2]$. The dynamic of the nutrient concentrations is
619 defined by:

$$620 \frac{dN_\ell}{dt} = D(S_\ell - N_\ell) - v_\ell \sum_i r_i G_i P_i,$$

621 Where $D = 0.25$ determines the nutrients turnover rate and $S_\ell = 5$ determines the maximal
622 nutrient level. The loss of a specific nutrient ℓ is limited by its relative content in the plant
623 "'species' biomass ($v_1=1$, $v_2=0.5$).

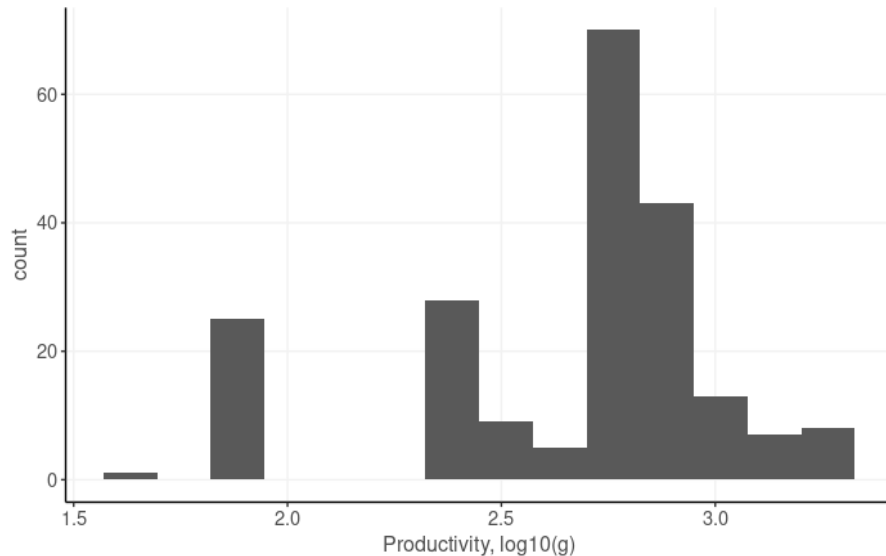
624 We ran our model on food webs of 50 species, composed of 30 consumers and 20 basal
625 species. A link was drawn between two species i and j when $L_{ij} > 0$. For each temperature we
626 ran 50 replicates of the two model's versions (with and without adaptive behaviour) and
627 recorded the number of extinctions. We fitted a GAM model on this number of extinctions
628

629 **Supplementary information II: Environmental characteristics**

630

631 Overall, the different environments considered were characterised by two contrasted levels of
632 productivity, leading to a bimodal distribution.

633



634

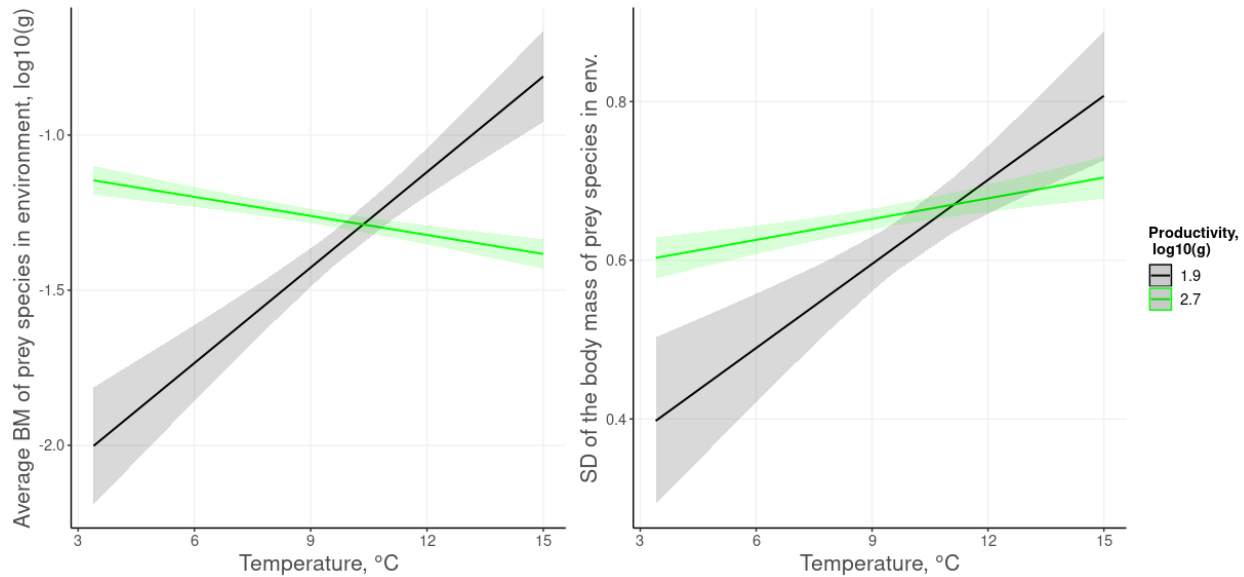
635 Fig. SI 2.1: distribution of the productivity values (g) for the different environments

636

637

638 Associated to these differences, we observed that the body mass distribution of the basal
639 species (median and standard deviation) was responding differently to temperature depending
640 on productivity values (Figure SI 2.2, Table SI 2.1):

641



642

643 Fig. SI 2.2: response of the body mass structure of the resource species to temperature and
 644 productivity

645

646 Table SI 2.1: model estimate for the prediction of median and standard deviation of the environment distributions

Predictors	Median of BM				Standard deviation of BM		
	Estimates	CI	p	Estimates	CI	p	
(Intercept)	-5.38	-6.32 – -4.43	<0.001	-0.43	-0.95 – 0.10	0.113	
Productivity	1.59	1.24 – 1.94	<0.001	0.37	0.17 – 0.57	<0.001	
Temperature	0.39	0.30 – 0.49	<0.001	0.10	0.05 – 0.15	<0.001	
productivity:temperature	-0.15	-0.19 – -0.12	<0.001	-0.03	-0.05 – -0.01	0.001	
Observations	223			223			
R ² / R ² adjusted	0.306 / 0.297			0.160 / 0.148			

647

648

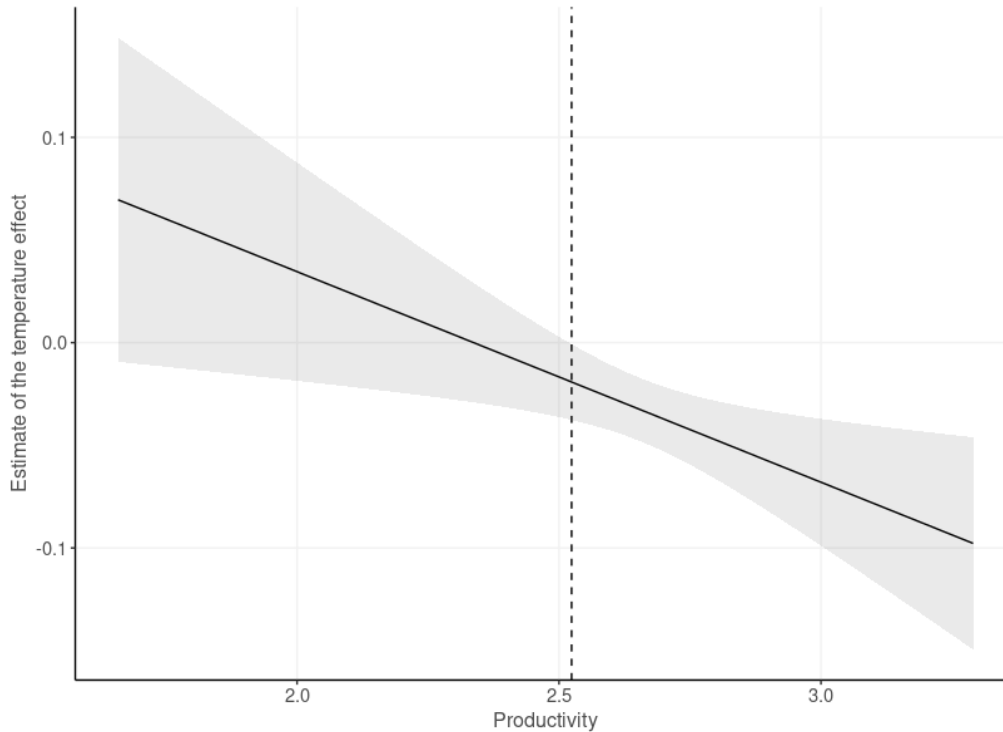
649

650 **Supplementary information III: response of the preferred distribution**
651 **to temperature at different levels of productivity**

652

653 As we observed a strong interaction effect between temperature and productivity when
654 explaining the response of the median of the body mass distributions in our different
655 environments, we estimated for which levels of productivity the relationship between
656 temperature and median was significant. At low productivity, we observed a positive slope
657 between the median and temperature albeit not significant. The slope of the regression linearly
658 decreased with productivity value, and became significantly lower than 0 for productivity levels
659 larger than $10^{2.52}$.

660



661

662 Fig. SI 3.1: Estimate and CI for the temperature effect at different levels of productivity. the
663 dashed line indicates the productivity value above which the temperature effect become
664 significant

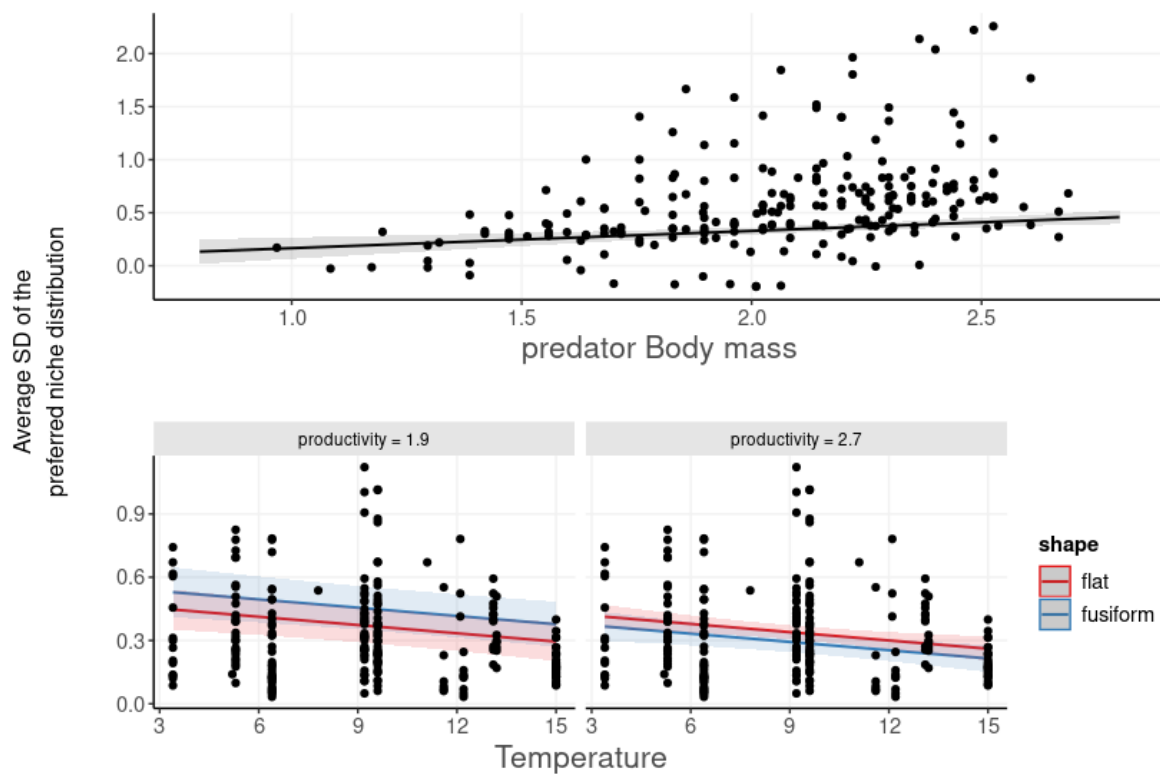
665

666

667 **Supplementary information IV: response of the width of the preferred**
668 **trophic niche to local conditions**

669

670 To assess how the width of the preferred niche responded to environmental conditions we fitted
671 the same models as for the median on the standard deviation of the body mass of the preferred
672 distribution. We observed that the standard deviation was decreasing with the predator body
673 mass and with temperature. We however detected an interaction between fish shape and
674 productivity. At low productivity levels the width of the trophic niche of fusiform fish tended to be
675 larger than the one of flat fish while the opposite is observed at higher productivity levels.



676

677 Fig. SI 4.1: Response of the width (standard deviation) of the preferred distribution to predator
678 body mass (a) and temperature for different productivity gradients (b,c). Colours define the fish
679 shape.

680

681 *Table SI 4.1: model estimates for the prediction of the standard deviation of the preference distributions*

<i>Predictors</i>	sd of the preference distribution		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	0.238	-0.075 – 0.551	0.135
Predator body mass	0.163	0.078 – 0.247	<0.001
Productivity	-0.043	-0.139 – 0.054	0.384
shapefusiform	0.387	-0.027 – 0.802	0.067
Temperature	-0.013	-0.021 – -0.005	0.001
productivity:shapefusiform	-0.161	-0.314 – -0.007	0.041
Observations	223		
R ² / R ² adjusted	0.137 / 0.118		

682

683

684

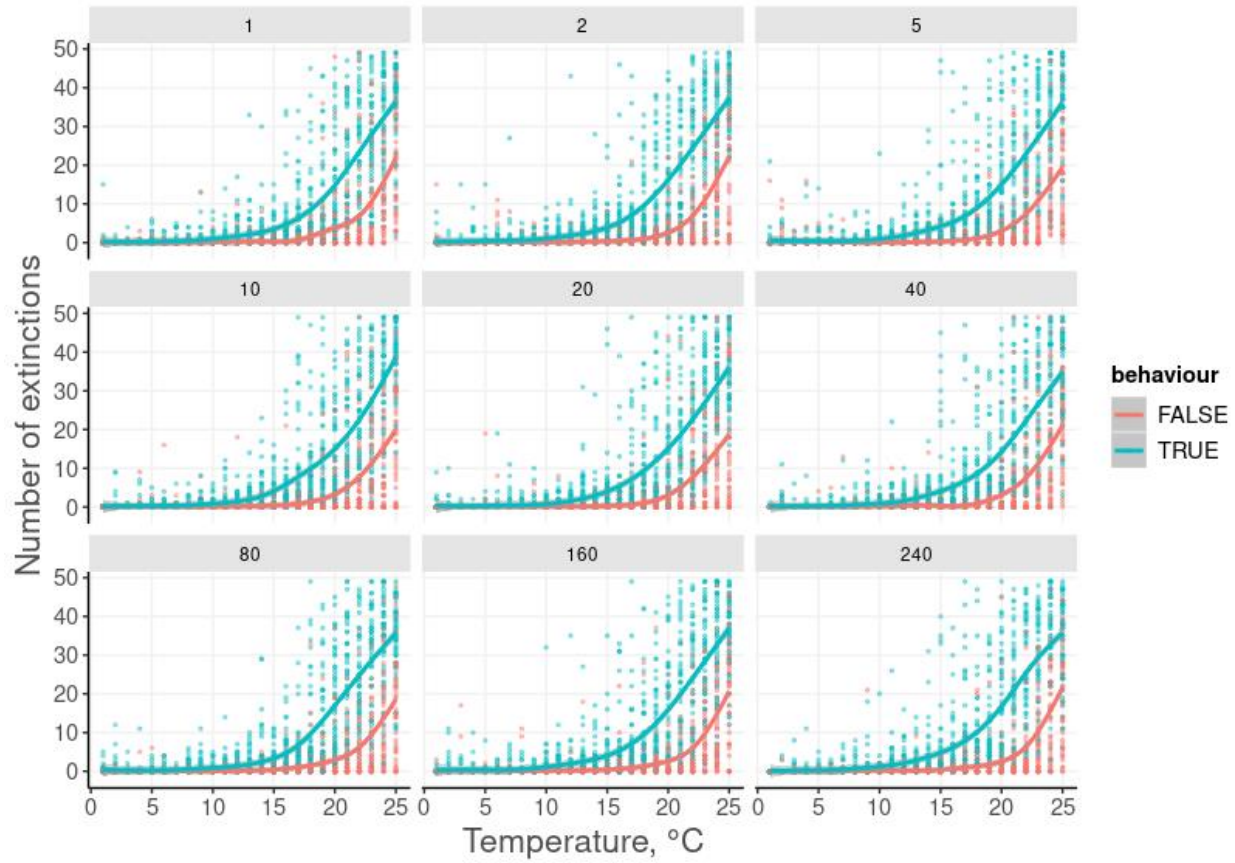
685 **Supplementary information V: Effect of nutrient availability and**
686 **predators' functional responses type on predictions about species**
687 **coexistence.**

688

689 As maximum nutrient availability (variable S_i) and shape of the functional response (q) are not
690 empirically informed, we analysed how sensitive to these two parameters model's predictions
691 are. We varied S_i from 1 to 240 and q from 0 to 0.5. Overall, we observed a very limited effect of
692 nutrient availability on the pattern observed (Fig. SI5.1). The type of the functional response
693 used resulted in more variations on the number of extinctions observed, but did not altered the
694 differences observed due to the incorporation of foraging behaviour (Fig. SI5.2).

695

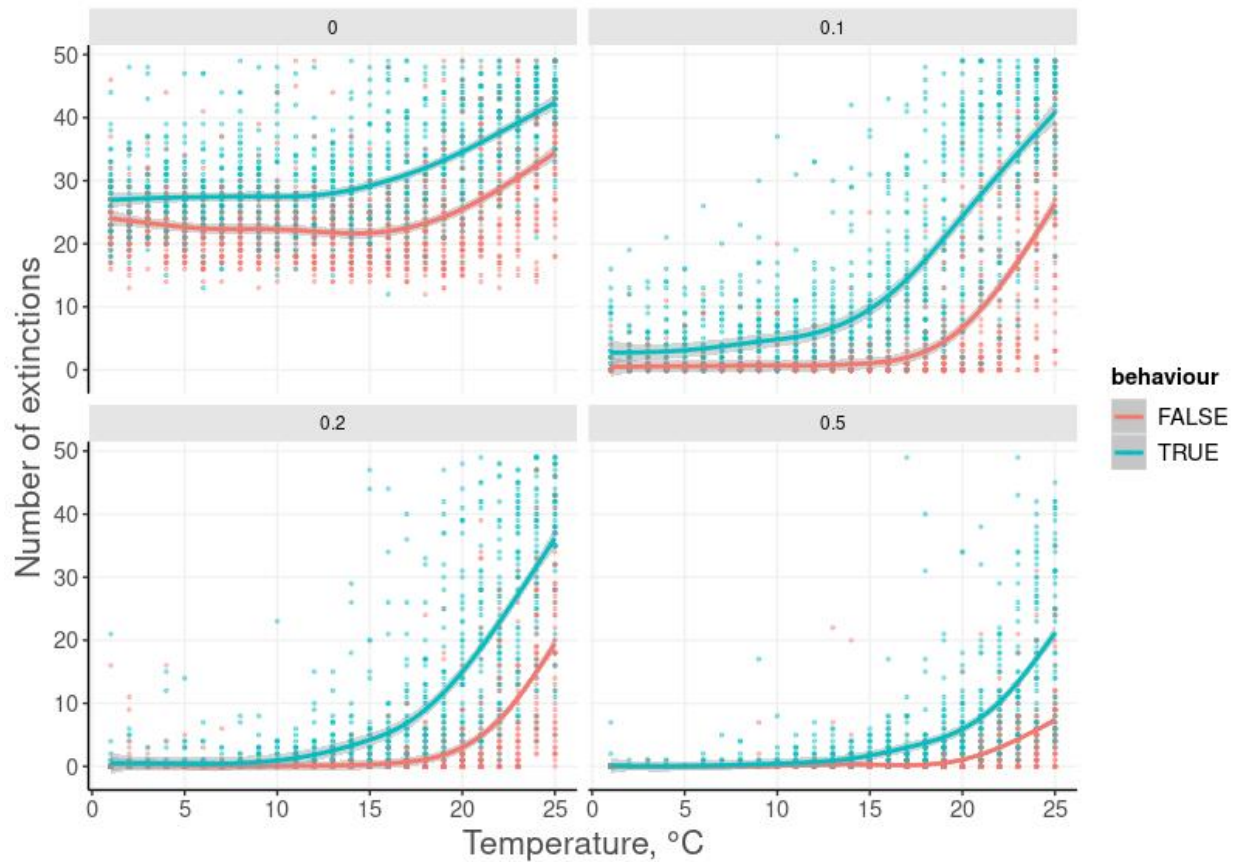
696



697

698 Figure SI 5.1: Effect of different levels of nutrient availability on the number of extinctions
699 predicted by the model. Simulations where ran with a hill exponent (q) of 0.2

700



701

702 Figure S15.2: effect of the choice of functional response type on the number of extinctions
703 predicted by the model. Simulations where ran for a level of maximum nutrient (S) of 5.

704

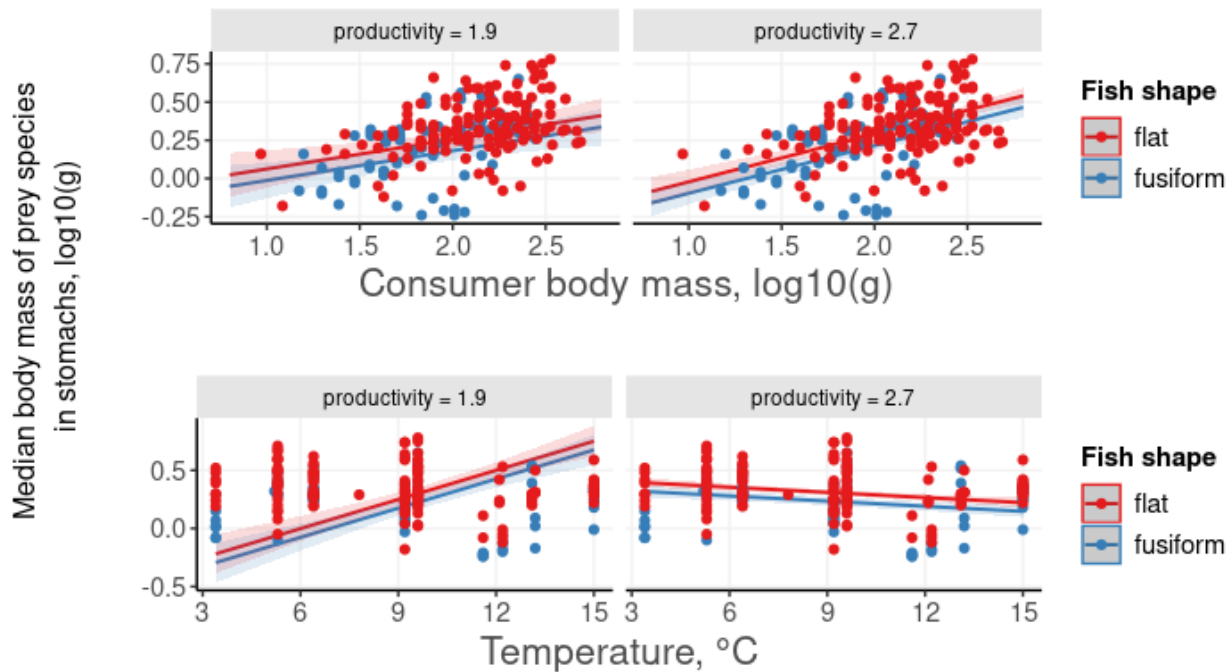
705

706 **Supplementary information VI: Effect of considering different**
707 **detection probabilities for prey in stomachs**

708
709 As prey composed of soft tissues only are supposed to be less likely to be detected because of
710 a faster digestion time, we corrected our observation by multiplying the abundance of species
711 with hard body parts by 0.8. This was done to mirror the importance of these species that
712 should persist longer in stomachs. As we are missing a general framework to properly describe
713 how digestion time changes for the different species we used a unique correction factor that is a
714 free parameter in our model (prey are either easy or difficult to digest, Table SI 6.3). We here
715 present the results we would have obtained without using this correction factor.

716
717

Results for the realised distributions



718
719 *Figure SI6.1: Response of the median body mass of the realised prey body mass distribution to predator body mass*
720 *(a, b), temperature (c, d) at different productivity levels for the two fish shape. Points represent non-transformed data*
721 *and lines present model predictions. The shaded areas show the 95% confidence interval on the predicted values.*
722 *Colours represent the fish functional groups (flat versus fusiform).*

723
724

Table SI6.1: response of the realised distribution to predator body mass and environmental gradients

<i>Predictors</i>	Median of the realised distribution		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	-2.57	-3.64 - -1.50	<0.001
Predator body mass	-0.09	-0.47 - 0.29	0.649
Productivity	0.88	0.47 - 1.28	<0.001
Shape (fusiform)	-0.08	-0.12 - -0.03	0.001
Temperature	0.32	0.24 - 0.40	<0.001
pred. BM:Productivity	0.15	0.00 - 0.30	0.048
Productivity:Temperature	-0.12	-0.15 - -0.09	<0.001
Observations	224		
R ² / R ² adjusted	0.450 / 0.435		

We can observe that the absence of correction factor does not qualitatively change the trends observed for the realised distributions. The variables selected by the AIC criteria are the same when correction for detectability was used. We can only detect slight changes in the model estimates.

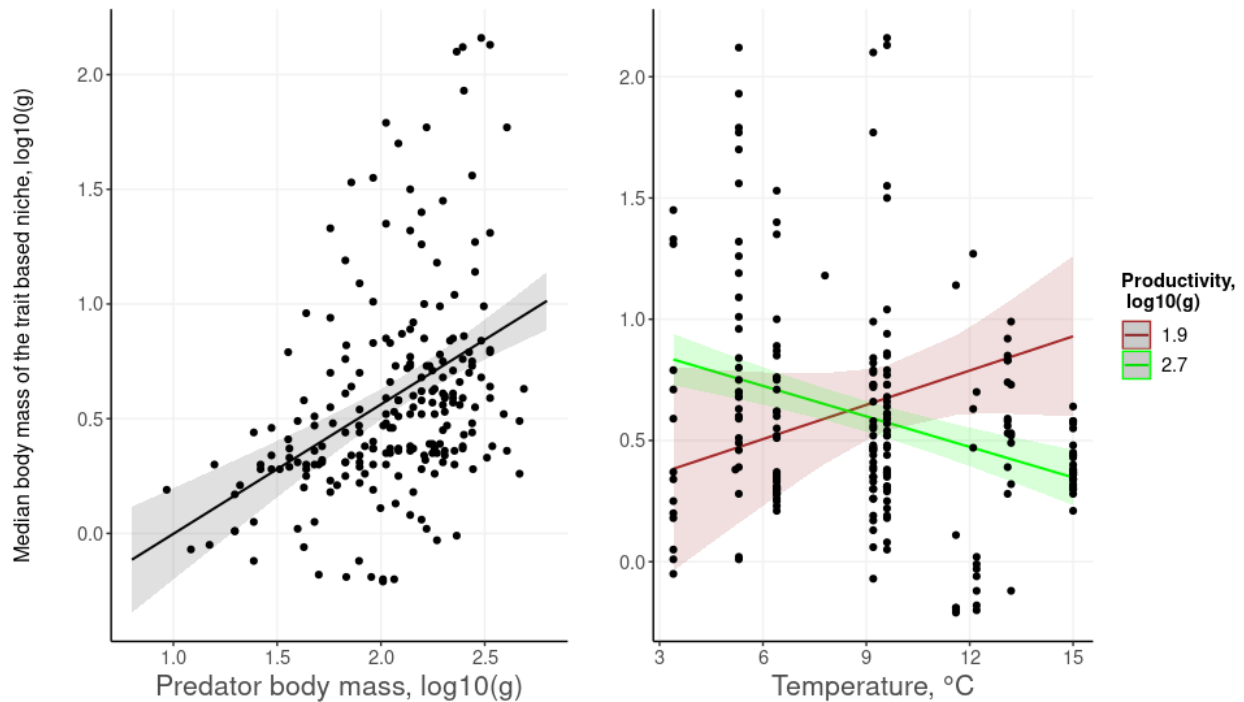
734

735

736

Response of the preference distribution

737



738

739 Figure SI6.2: Response of the median body mass of the preference distribution to temperature,
 740 productivity, and fish body mass. Points represent non-transformed data and lines represent
 741 model predictions. The shaded areas show the 95% confidence interval on the predicted values.
 742 Grey and green colour represent two different productivity levels at which the temperature effect
 743 is represented

744

745

Table SI 6.2: response of the preference distribution to predator body mass and environmental gradients

746

<i>Predictors</i>	Median of the preference distribution		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	-1.252	-3.954 - 1.450	0.362
Predator body mass	-0.153	-1.115 - 0.809	0.754
Productivity	0.392	-0.631 - 1.414	0.451
shapefusiform	-0.124	-0.238 - -0.011	0.032
Temperature	0.259	0.051 - 0.466	0.015
pred.BM:productivity	0.268	-0.103 - 0.639	0.156
Productivity:Temperature	-0.111	-0.189 - -0.033	0.005
Observations	224		
R ² / R ² adjusted	0.282 / 0.262		

We observed here a change in the model output. The effects of predator body masses and productivity on the median of the preference distributions are not significant anymore. This is likely due presence of the new significant effect of the interaction between these two variables, as we can observe that the plots remain quite similar (Fig.

756 SIVI.2).

757

758

759 **Classification of species' digestibility**

760

Prey species	Class	Digestibility
<i>Abra alba</i>	Bivalvia	Hard
<i>Aloidis gibba</i>	Bivalvia	Hard
<i>Amphicteis gunneri</i>	Polychaeta	Easy
<i>Amphipoda</i> spp.	Malacostraca	Easy
<i>Anaitides</i> spp.	Polychaeta	Easy
<i>Anthozoa</i> spp.	Anthozoa	Easy
<i>Aphia minuta</i>	Actinopterygii	Hard
<i>Aphroditidae</i> spp.	Polychaeta	Easy
<i>Arenicola marina</i>	Polychaeta	Easy
<i>Ascidacea</i> spp.	Ascidacea	Easy
<i>Astarte</i> spp.	Bivalvia	Hard
<i>Balanus</i> spp.	Hexanauplia	Hard
<i>Brada villosa</i>	Polychaeta	Easy
<i>Capitella capitata</i>	Polychaeta	Easy
<i>Carcinus maenas</i>	Malacostraca	Hard
<i>Cardium fasciatum</i>	Bivalvia	Hard
<i>Castalia punctata</i>	Polychaeta	Easy
<i>Clupea harengus</i>	Actinopterygii	Hard

Corophium spp.	Malacostraca	Easy
Crangon crangon	Malacostraca	Hard
Cumacea spp.	Malacostraca	Easy
Mysidacea spp.	Malacostraca	Hard
Cyprina islandica	Bivalvia	Hard
Diastylis rathkei	Malacostraca	Easy
Disoma multisectosum	Polychaeta	Easy
Euchone papillosa	Polychaeta	Easy
Gastosaccus spinifer	Malacostraca	Hard
Gobiidae spp.	Actinopterygii	Hard
Halicryptus spinolosus	Halicryptomorpha	Hard
Harmothoe imbricata	Polychaeta	Easy
Harmothoe spp.	Polychaeta	Easy
Hyperia galba	Malacostraca	Easy
Idothea spp.	Malacostraca	Hard
Isopoda spp.	Malacostraca	Hard
Limanda limanda	Actinopterygii	Hard
Macoma spp.	Bivalvia	Hard
Metridium senile	Anthozoa	Hard
Microdeutopus sp.	Malacostraca	Easy
Musculus spp.	Bivalvia	Hard
Mya truncata, Mya arenaria	Bivalvia	Hard
Mysis mixta	Malacostraca	Hard
Mytilus edulis	Bivalvia	Hard
Nemertea spp.	Nemertea	Easy
Nephtys spp.	Polychaeta	Easy
Nucula nitida	Bivalvia	Hard
Ophiura albida	Ophiuroidea	Hard
Other Decapoda	Decapoda	Hard
Other Gastropoda	Gastropoda	Hard
Other Polychaeta	Polychaeta	Easy
Pectinaria koreni	Polychaeta	Easy
Phaxas pellucidus	Bivalvia	Hard
Pherusa plumosa	Polychaeta	Easy
Phtisica marina, Caprella	Malacostraca	Easy
Pisces spp.	Actinopterygii	Hard
Pleuronectiformes spp.	Actinopterygii	Hard
Polydora sp.	Polychaeta	Easy
Pomatoschistus minutus	Actinopterygii	Hard

Priapulus caudatus	Priapulida	Easy
Saxicava arctica	Bivalvia	Hard
Scoloplos armiger	Polychaeta	Easy
Spionidae spp.	Polychaeta	Easy
Terebellides stroemi	Polychaeta	Easy
Thyonidium pellucidum	Holothuroidea	Hard