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4 **Title**

5 Disentangling diverse responses to climate change among global marine ecosystem models

6

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55

56 **Abstract**

57 Climate change is warming the ocean and impacting lower trophic level (LTL) biomass and  
58 production. Marine ecosystem models can provide projections of how climate change will  
59 impact societal services such as fisheries, but these estimates vary widely. A better  
60 understanding of what drives this variation will improve our ability to project fisheries and  
61 other ecosystem services into the future, while also helping to identify uncertainties in  
62 process understanding. Here, we explore mechanisms driving the diversity of responses to  
63 changes in temperature and LTLs in eight global marine ecosystem models from the Fisheries  
64 and Marine Ecosystem Model Intercomparison Project (FishMIP). Temperature and LTL  
65 impacts on total consumer biomass and ecosystem structure (defined as the relative change  
66 of small and large organism biomass) were isolated using a comparative experimental  
67 protocol. Total model biomass varied between -35% to +3% in response to warming, and -  
68 17% to +15% in response to LTL changes. There was little consensus about the spatial  
69 redistribution of biomass or changes in the balance between small and large organisms  
70 (ecosystem structure) in response to warming, and LTL impacts on total consumer biomass  
71 varied depending on the choice of LTL forcing terms. Overall, climate change impacts on  
72 consumer biomass and ecosystem structure are well approximated by the sum of  
73 temperature and LTL impacts, indicating an absence of nonlinear interaction between the

74 models' drivers. Our results highlight a lack of theoretical clarity about how to represent  
75 fundamental ecological mechanisms, most importantly how temperature impacts scale from  
76 individual to ecosystem level, and the need to better understand the two-way coupling  
77 between LTL organisms and consumers. We finish by identifying future research needs to  
78 strengthen global marine ecosystem modelling and improve projections of climate change  
79 impacts.

80

81 **Keywords**

82 *Climatic change, modelling, fishery oceanography, marine ecology, FishMIP, structural*  
83 *uncertainty*

84

85

## 86 **1. Introduction**

87 Water temperature and primary production play critical roles in marine processes. Higher  
88 temperatures accelerate reaction rates, with consequences ranging from the molecular to  
89 ecosystem scale, while primary production provides the fundamental source of energy for  
90 almost all marine life (Brown et al. 2004; Chavez et al. 2011). Climate change impacts on both  
91 water temperature and primary production will thus alter marine ecosystems in fundamental  
92 ways (Pörtner et al. 2014). For example, a first-order expectation of these impacts is that  
93 accelerated metabolic rates will consume energy more quickly in a warmer ocean, all else  
94 being equal, so that less biomass could be supported by a given level of primary production  
95 (Heneghan et al, 2019). Yet, ecosystem-level effects emerge from individual-level processes  
96 and interactions, which could lead to nonlinear effects and changes in ecosystem structure,  
97 while shifting thermal habitats may influence the distribution of species, transforming food-  
98 webs to previously unknown states (Coll et al. 2020; Pinsky et al. 2020; Poloczanska et al.  
99 2016).

100

101 There is a growing need to quantify and project climate change impacts on marine ecosystems  
102 to motivate mitigation (Bryndum-Buchholz et al. 2020), provide insight into potential future  
103 threats to food security (Barange et al. 2014; Blanchard et al. 2017a; Boyce et al. 2020), and  
104 identify needs for biodiversity conservation (Brito-Morales et al. 2020; Waldron et al. 2020).  
105 Thus, there has been a recent proliferation of spatially-explicit marine ecosystem models that  
106 simulate higher trophic level biomass and ecosystem structure at regional and global scales,  
107 driven by output from climate-ocean-biogeochemical models (Tittensor et al. 2018). These  
108 ecosystem models differ significantly in their design, level of complexity and implementation,  
109 reflecting different choices for how to represent fundamental marine ecosystem processes,

110 as well as a diversity of model purpose and scope. As a result, there is considerable  
111 uncertainty in model projections of climate change impacts on higher trophic levels (e.g. Lotze  
112 et al., 2019), with projections from each model dependent upon decisions around inclusion  
113 or simplification of processes. Structural diversity in model projections is a strength for  
114 gaining a rich view of possible outcomes, given that each model reflects a different subset of  
115 established physiological and process knowledge, implemented using different mathematical  
116 representations (Knutti, 2010; Brander et al. 2013; Lefevre et al. 2017; Payne et al. 2016). At  
117 the same time, this diversity reflects fundamental uncertainty in our understanding of  
118 processes. Thus, identifying sources of structural uncertainty in ensemble projections can  
119 point to critical weaknesses and thereby accelerate model improvement.

120

121 The Fisheries and Marine Ecosystem Model Intercomparison Project (FishMIP) was created to  
122 explore this uncertainty and provide more robust assessments of climate impacts on marine  
123 ecosystems through the analysis of multi-model ensembles (Tittensor et al. 2018). A recent  
124 FishMIP study (Lotze et al. 2019) found that projections of mean changes in animal biomass  
125 from a model ensemble typically compared better with empirical data than individual models,  
126 emphasising the benefits of ensemble climate impact projections. However, uncertainty in  
127 ensemble projections of higher trophic level biomass is significant: Lotze et al. (2019) found  
128 that the spread of changes across the FishMIP ensemble in 21st century marine consumer  
129 biomass under the high emissions, representative concentration pathway 8.5 (RCP8.5)  
130 climate change scenario (0 to -35%) was larger than the multi-model mean consumer biomass  
131 change between the RCP2.6 (low emissions) and RCP8.5 scenarios (-5% to -20%). This means  
132 that structural uncertainty across global marine models is greater than climate scenario

133 uncertainty, which is problematic for the goal of using these models to provide assessments  
134 of climate impacts on marine ecosystems and the societal services they provide.

135

136 For all global models in the FishMIP ensemble, temperature and lower trophic level (LTL)  
137 forcings such as net primary production, phytoplankton and zooplankton biomass, and export  
138 carbon are the two main drivers of projected climate change impacts (Tittensor et al. 2018),  
139 yet their implementations vary. Although there is some agreement on how temperature  
140 impacts physiological processes in general (e.g. Kooijman, 2010), there is less agreement on  
141 how these impacts vary across functional groups, body sizes, and different processes such as  
142 growth and metabolism (van Denderen et al. 2020). Similarly, although it is universally  
143 understood that LTL biomass and production provide the source of energy that supports  
144 higher trophic levels, there is less understanding about how the physiology and structure of  
145 LTLs affects transfer efficiency and ecosystem structure, and how to couple lower and higher  
146 trophic levels (Eddy et al. 2020; Heneghan et al. 2016; Stock et al. 2017). Previous multi-model  
147 ensemble studies have explored structural model uncertainty in projections of consumer  
148 biomass and species distribution shifts under climate change (e.g. Jones et al. 2012;  
149 Woodworth-Jefcoats et al. 2015), but these studies did not disentangle the effects of  
150 temperature and lower trophic level (LTL) changes, a strategy that can provide mechanistic  
151 insight on underlying processes (Carozza et al. 2018).

152

153 Here, we identify sources of structural uncertainty in marine ecosystem models, by  
154 disentangling the effects of temperature and LTL changes on model projections using eight  
155 global models from the FishMIP ensemble. We first summarise how temperature and LTL  
156 processes are incorporated in these models, highlighting common representations and

157 differences across the ensemble. We then isolate the impact of changes in temperature and  
158 LTL processes on consumer biomass and ecosystem structure (which we define as the relative  
159 change in small <30 cm and large  $\geq$ 30 cm consumer biomass) in a simulation protocol  
160 involving a combination of pre-industrial, historical and RCP8.5 forcings. By illuminating key  
161 sources of structural uncertainty in marine model projections, we identify critical areas of  
162 future research necessary to improve not only climate impact projections but also our  
163 understanding of the marine ecosystem.

164

## 165 **2. Methods**

166 We used projections from eight marine ecosystem models from the Fisheries and marine  
167 ecosystem Model Intercomparison Project (FishMIP, [www.fishmip.org](http://www.fishmip.org); Tittensor et al. 2018).

168 There are several model types (see Tables 1 and 2 for a summary of each model and key  
169 references). First, models that draw on the strongly size-structured nature of marine  
170 ecosystem processes to represent the ecosystem purely by body size (BOATS,  
171 Macroecological) or trophic level (EcoTroph). Second, trait-based size-structured models  
172 (APECOSM, DBPM, FEISTY, ZooMSS), which move beyond a purely size-based representation  
173 to include different communities and groups using functional traits other than body size. Last,  
174 DBEM is a habitat suitability-based species-distribution model that resolves the biomass and  
175 spatial distribution of >1200 fish and invertebrate species using observational data, and  
176 includes other mechanisms such as species ecophysiology and dispersal. There is large  
177 variation in the structural complexity of the models, and a detailed description of how each  
178 model incorporates temperature and lower trophic level (LTL) impacts, including relevant  
179 equations and temperature parameters, can be found in the Supplementary Information S2.

180 Here we summarise the key similarities and differences of each model as they pertain to



181 temperature, LTLs and other drivers in Sections 2.1, 2.2, 2.3 and Table 1 and 2. We then  
182 explain the experimental protocol and model outputs in Section 2.4.

183

## 184 **2.1. How do models incorporate temperature impacts?**

185 Across all models, individuals gain mass through anabolic processes such as food uptake and  
186 assimilation, while they lose mass through catabolic processes such as respiration.

187 Populations can also gain individuals through reproduction, and lose individuals through  
188 mortality (Table 2). These processes are all influenced by temperature. As a result, changes

189 in ecosystem structure depend on how models resolve: (i) temperature effects on individual  
190 anabolic and catabolic processes across different functional groups, body sizes or trophic  
191 levels; and (ii) how these variations drive changes in ecological interactions (Table 2).

192 Temperature effects on these processes are represented in all models as an exponential  
193 scaling, with parameters varying widely between models (Supplementary Information S2).

194 However, within models the same temperature scaling parameters are used across all  
195 functional groups and ecosystem components, excluding EcoTroph, which uses different  
196 scalings depending on the ecosystem's biome.

197

198 The representation of anabolic and catabolic processes varies across models (Table 2).

199 Macroecological and EcoTroph have the simplest representations, with individual mass

200 changes resolved implicitly in each model by a single individual metabolic rate that scales with

201 temperature and body size (for Macroecological) or trophic level (for EcoTroph). For these

202 models, total biomass at a given body size/trophic level is determined by the metabolic

203 carrying capacity of that size/trophic level, divided by the metabolic rate of individuals. In

204 these two models, individual metabolic rates increase with temperature while total metabolic

205 carrying capacity at a given body size/trophic level is determined by net primary production.  
206 Thus, as warming drives an increase in individual metabolism, total biomass decreases even  
207 if primary production remains constant. The BOATS model uses a similar framework to  
208 Macroecological and EcoTroph to determine maximum supported biomass at each body size  
209 class. However, in BOATS individual mortality is resolved separately and the growth of  
210 individuals from one size class to the next is explicitly resolved. As temperatures rise,  
211 individual growth rates in BOATS increase, increasing the speed of biomass flow from small  
212 to large size classes, but also increasing mortality and reducing the maximum biomass that  
213 can be supported at each body size. Taken together, these processes mean that warming  
214 causes total biomass to decrease in BOATS.

215

216 Within BOATS, Macroecological and EcoTroph, ecological interactions such as predator-prey  
217 encounters or predator-predator competition are not explicitly resolved. Thus, temperature  
218 and LTL drivers do not explicitly change interactions among individuals. However, in BOATS  
219 and Macroecological, all primary producers are represented by a single body size, which is  
220 inversely related to temperature; as temperature increases, the single representative body  
221 size of primary producers decreases according to an empirical equation. This in turn decreases  
222 the production of higher trophic level organisms, as the number of trophic steps that net  
223 primary production must be transferred through to reach any given body size increases.  
224 However, since trophic transfer efficiency in these models is not temperature-dependent, an  
225 increase in the number of trophic levels is not expected to change the ratio of small and large  
226 organism biomass. In contrast, transfer efficiency decreases with warming in Ecotroph. This  
227 means that warmer waters in Ecotroph will support relatively less biomass at high trophic  
228 levels (large body sizes) than what they will at low trophic levels (small body sizes).

229

230 For trait-based models (APECOSM, DBPM, FEISTY and ZooMSS), individual growth is fuelled  
231 by ingesting smaller organisms, with individual ingestion rates scaling with temperature and  
232 body size. For APECOSM, DBPM and FEISTY this scaling is also modulated with the density of  
233 prey. Thus, food uptake for individuals at one size is fuelled by predation of smaller size  
234 individuals, and in some cases predators can compete with each other for the same prey.  
235 These models also include other sources of mortality (destruction of population biomass).  
236 APECOSM, DBPM and ZooMSS incorporate at least one size-dependent mortality term, and  
237 FEISTY includes a single natural mortality term that is independent of body size. These  
238 additional mortality sources increase with temperature (except for senescence mortality in  
239 DBPM and natural mortality in FEISTY), causing population biomass to decrease with  
240 increasing temperature. In FEISTY, maintenance costs increase faster with both body size and  
241 temperature than do ingestion rates. APECOSM and FEISTY also explicitly resolve size and  
242 temperature-dependent costs of maintaining existing biomass (metabolism). In these models,  
243 as temperature increases, maintenance costs also increase, reducing the available energy for  
244 growth and reproduction. If maintenance costs of existing biomass exceed energy intake from  
245 ingestion, biomass decreases. As food becomes limited in APECOSM, ingestion rates scale  
246 more slowly with temperature than maintenance costs, limiting the scope for new growth  
247 and potentially inducing biomass to decrease as maintenance costs outpace ingestion.

248

249 In APECOSM, DBPM, FEISTY and ZooMSS, temperature affects anabolic and catabolic  
250 processes differently across ecosystems, which has cascading effects on how the different  
251 components of ecosystems (e.g. predators and preys) interact. In APECOSM, FEISTY and  
252 ZooMSS for example, the scaling of maintenance costs (in APECOSM and FEISTY) and

253 senescence mortality (in APECOSM and ZoomSS) with body size and temperature mean that  
254 large organisms are more vulnerable to warming compared to small organisms. Everything  
255 else being equal, a warming-induced decrease in large organism biomass would reduce  
256 predation mortality on smaller organisms, thus favouring small organisms in these models.

257

258 Unlike what happens in the size and trait-based models, anabolic and catabolic processes in  
259 DBEM are not driven explicitly by net primary production or by the ingestion of smaller  
260 organisms. Instead, individual mass increases in DBEM when anabolism exceeds catabolism,  
261 both of which are affected by temperature and other drivers (see Section 2.3). Similar to  
262 APECOSM, FEISTY and BOATS, the explicit balance between anabolic and catabolic processes  
263 drives an organism's scope for growth—if catabolism outpaces anabolism, an individual's mass  
264 will decline. In DBEM, anabolism accelerates more slowly with warming compared to  
265 catabolism. Thus, as waters war, an organism's scope for growth becomes increasingly  
266 limited, and their maximum size decreases.

267

268 Organisms do not interact in DBEM. Rather, temperature and other forcings drive the spatial  
269 distribution of species across the ocean, with species' relative abundance in a region changing  
270 with respect to temperature depending on their thermal preference, and the prevailing water  
271 temperature. Thus, as waters warm, ecosystem structure changes by individual organisms  
272 becoming smaller on average, and by different species shifting their spatial boundaries to  
273 follow their thermal preferences.

274

275 Finally, energy transfer from small to large organisms through size-based predation is not the  
276 only way that different parts of the ecosystem interact; in APECOSM, BOATS, DBPM, DBEM

277 and FEISTY, energy moves from large to the smallest size classes through reproduction. In  
278 these models, the flux of small organism biomass entering the population through  
279 reproduction can increase or decrease, depending on the relative impacts of warming on large  
280 organisms. In FEISTY for example, if large organisms are more adversely affected by warming  
281 than small organisms, the reproduction rate in larger size classes would also decline, leading  
282 to less biomass overall.

283

## 284 **2.2. How do models incorporate lower trophic level processes?**

285 Net primary production sustains essentially all non-photosynthetic life in the oceans, and  
286 limits the biomass of higher trophic levels (Chavez et al. 2011). Solar energy captured and  
287 organic matter synthesized by primary producers flow through the food webs, primarily by  
288 larger organisms preying on smaller organisms. FishMIP models focus on higher trophic levels,  
289 so lower trophic level processes are driven by a range of Earth system model forcings (Table  
290 1). The role of lower trophic levels in setting the limits to growth for higher trophic levels is  
291 represented across the eight FishMIP models in two ways. First, for BOATS, DBEM,  
292 Macroecological and Ecotroph, net primary production is used to determine limits of  
293 consumer growth rates and total biomass according to trophic transfer functions. Second, in  
294 the trait-based models (APECOSM, DBPM, FEISTY and ZoomSS), plankton biomass and export  
295 production are consumed by the size classes or functional groups that feed on them. This  
296 energy is then transferred to higher trophic levels through size-based predation. However, all  
297 eight models considered here are one-way forced (run offline), so there is no feedback from  
298 higher trophic levels to lower trophic level biomass or production. This means that for the  
299 trait-based models, ingestion-fuelled growth of higher trophic level predators is not explicitly  
300 matched by predation mortality in the plankton.

301

302 The correlation of mean phytoplankton size with total primary production is an important  
303 driver of ecosystem structure (Boyce et al. 2015). Phytoplankton are generally larger in more  
304 productive waters (Barnes et al. 2011; Finkel et al. 2010). Given the size-structured nature of  
305 the marine ecosystem (Trebilco et al. 2013), smaller phytoplankton support longer food  
306 chains, which are thought to support relatively less consumer biomass (Eddy et al. 2020;  
307 Ryther, 1969). All models explicitly represent this phenomenon with the exception of  
308 EcoTroph and DBEM. EcoTroph uses trophic level instead of body size to represent the marine  
309 ecosystem. In DBEM, changes in net primary production affect the carrying capacity of  
310 modelled species disregarding the size of primary producers. In BOATS and Macroecological,  
311 changes in food chain length are represented by a varying representative size of  
312 phytoplankton, the size increasing with net primary production according to empirical  
313 equations. In DBPM and ZooMSS, the phytoplankton size-spectrum, which is the relationship  
314 between primary producer abundance  $N$  and body size  $w$ ,  $N = aw^b$ , is continuous, with the  
315 intercept  $a$  and slope  $b$  set by phytoplankton biomass. In these two models, the plankton size-  
316 spectrum intercept is lower and the slope is steeper in less productive waters, meaning  
317 relatively more small producers but less biomass overall. APECOSM and FEISTY use size-  
318 fractionated phytoplankton and zooplankton biomass inputs from earth system models to  
319 directly set the biomass of small and large phytoplankton and zooplankton groups, with a  
320 fixed size-spectrum slope assigned to each LTL group in APECOSM. APECOSM and FEISTY also  
321 use export carbon to represent detrital flux across the entire water column (in APECOSM) or  
322 to the seafloor to fuel the growth of benthic invertebrates (in FEISTY).

323

324

325 **2.3. How do models incorporate other impacts?**

326 All models in the FishMIP ensemble are driven solely by temperature and LTL drivers, with  
327 the exception of APECOSM and DBEM (Table 1). In these two models, movement of organisms  
328 between adjacent grid cells is resolved, so both models incorporate current speeds. Since  
329 APECOSM resolves the 3D density of animal biomass, the model also uses 3D  
330 photosynthetically active radiation to resolve water clarity and light penetration across the  
331 water column. Thus, in APECOSM areas with the highest consumer biomass are not  
332 necessarily regions with the highest LTL biomass, due to active and passive horizontal  
333 movements in response to temperature, light, food availability and the strength of currents.  
334 Both APECOSM and DBEM also incorporate oxygen concentration, which impacts anabolic  
335 processes; lower oxygen concentrations reduces the scope for organism growth in both  
336 models, and thus reduces total biomass. DBEM also resolves the negative impacts of  
337 acidification on catabolic processes, by incorporating pH forcings. DBEM also uses salinity, sea  
338 ice and mixed layer depth forcings, alongside temperature, to establish the spatial extent of  
339 each of the >1200 fish and invertebrate species the model resolves.

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348 **Table 1** Summary of temperature, lower trophic level (LTL) and other drivers sourced from  
 349 earth system models, used by each model in the FishMIP ensemble, as well as the ecosystem  
 350 representation of each model. All drivers used by the models in this experiment had a monthly  
 351 temporal resolution.

Model and key references	Temperature drivers	LTL drivers	Other drivers	Taxonomic scope
<b>APECOSM</b> Maury et al. 2007a; 2007b; Maury 2010; Maury and Poggiale, 2013	3D water temperature	3D small and large phytoplankton, 3D small and large zooplankton biomass*, 3D export carbon flux	3D oxygen concentration, 3D photosynthetically active radiation, 3D current velocities	All epipelagic, mesopelagic and migratory heterotrophic marine animals in the pelagic ecosystem between 15µg– 120kg.
<b>BOATS</b> Carozza et al. 2016; 2017	2D water temperature (averaged over top 75 m)	2D depth-integrated net primary production	NA	All commercial animal biomass from 10g–100kg.
<b>DBEM</b> Cheung et al. 2008; 2010; 2011; 2016	2D sea surface temperature	2D depth-integrated net primary production	2D surface and bottom oxygen concentration, salinity and pH, sea ice, mixed layer depth, 3D current velocities	>1200 fish and invertebrate species.
<b>DBPM</b> Blanchard et al. 2009; 2012	2D sea surface and bottom water temperature	2D depth-integrated small and large phytoplankton biomass	NA	All benthic and pelagic marine animals, weighing between 1mg and 1 tonne.
<b>EcoTroph</b> Gascuel and Pauly, 2009; du Pontavice et al. 2020	2D sea surface temperature	2D depth-integrated small and large phytoplankton biomass	NA	All marine animals with trophic level $\geq 2$ .
<b>FEISTY</b> Petrik et al. 2019	2D upper pelagic (averaged over 100 m) and bottom water temperature	2D depth-integrated (top 100 m) small and large zooplankton biomass*, 2D export carbon flux to the sea floor	NA	Forage, large pelagic and demersal fish, as well as benthic invertebrates, between 1mg and 125kg.
<b>Macroecological</b> Jennings and Collingridge (2015)	2D sea surface temperature	2D depth-integrated small and large phytoplankton biomass	NA	All marine animals between 1mg and 1 tonne.
<b>ZooMSS</b> Heneghan et al. (2020)	2D sea surface temperature	2D sea surface phytoplankton biomass	NA	Nine zooplankton groups, from flagellates to jellyfish and all fish and mammals between 1mg and 10 tonnes.

352 \* Where small and large zooplankton biomass are not provided by an earth system model (as  
 353 is the case with CESM1-BGC, the earth system model used in this study) FishMIP splits total  
 354 zooplankton biomass using the ratio of small and large phytoplankton biomass.  
 355

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357



**Table 2** Summary of temperature and lower trophic level impacts in the FishMIP model ensemble.

Model	Temperature effect on:		Lower trophic level effect on:	
	Individual anabolic and catabolic processes	Ecosystem structure	Individual anabolic and catabolic processes	Ecosystem structure
<b>APECOSM</b>	Ingestion and thus predatory mortality scales with temperature and varies with predator size and the density of prey. Assimilation, maintenance, and non-predation mortality rates also scale with temperature. Temperature effects largely balance where prey density is high. In food limited areas, catabolic processes increase faster than anabolic processes, causing individual mass to decrease.	Growth and mortality increase with temperature. In food limited situations, leading to less biomass, especially for large organisms. In prey rich regions, temperature does not drive biomass down but drives a faster transfer toward large sizes causing an increase in large organisms and a decrease of small organisms due to top-down control.	Small and large plankton biomass is the primary food source of small consumer organisms. More plankton biomass increases satiation and maximizes individual growth and reproduction, thus driving increases in biomass.	More plankton biomass supports more ecosystem biomass and reduces the trophic amplification of food limitation with size. This leads to biomass increase of large organisms and the presence of larger species in the communities.
<b>BOATS</b>	Warming drives higher individual growth and mortality rates, which reduces the maximum biomass that can be supported by a given level of primary production.	Phytoplankton size decreases with warming, lengthening food chains and reducing total energy transferred to higher trophic levels.	Net primary production sets the limits to growth across all body size classes. Higher production means more biomass.	Phytoplankton size decreases with decreasing production. Smaller phytoplankton mean longer food chains causing biomass declines for all sizes.
<b>DBEM</b>	Biomass creation occurs after catabolism is deducted from anabolism. Catabolism increases faster with warming than anabolism. Thus, biomass decreases with warming.	Catabolism increases with size faster than anabolism, so warming affects large species more and drives shifts in spatial distribution of species.	In all regions, net primary production is a key part of what sets the limits to maximum biomass across all higher trophic levels.	Lower net primary production means less consumer biomass can be supported.
<b>DBPM</b>	Ingestion-driven growth, and mortality rates from predation and natural sources scale with temperature at the same rate. Thus, temperature effects largely balance, except in low food regions where natural mortality is relatively large and causes biomass to decrease.	Natural mortality costs scale with temperature but decrease with body size. Thus, warming increases mortality relatively more for small organisms compared to large, potentially causing their biomass to decrease faster.	Small and large phytoplankton biomass set the slope and intercept of the phytoplankton size-spectrum, which is the primary food source of small pelagic organisms. More phytoplankton means more biomass.	Relatively more small phytoplankton with less phytoplankton biomass, which reduces food for small organisms and increases food chain length. Decreases overall biomass, especially for larger sizes, as senescence increases with size.
<b>EcoTroph</b>	Warming drives higher individual turnover rates, and lower trophic transfer efficiency, which means fewer individuals can be supported, causing biomass to decrease.	Trophic transfer efficiency decreases with warming, causing higher trophic level biomass to decrease more than lower trophic level biomass.	Net primary production is a driver of total biomass across all trophic levels. Higher production means more biomass.	Lower net primary production means less biomass can be supported across all trophic levels.
<b>FEISTY</b>	Maintenance costs, ingestion-driven growth, and mortality rates from predation scale with temperature. Maintenance costs increase faster with warming compared to ingestion, so warming reduces the scope for growth, causing biomass to decrease.	Maintenance costs increase faster than ingestion-driven growth with body size and temperature. Thus, warming will reduce the scope for large organism growth more than small organisms.	Zooplankton is food for all small consumers and medium pelagic consumers. Export production fuels benthic growth. More zooplankton biomass and export production means more ecosystem biomass overall.	Less zooplankton biomass, composed of relatively more small zooplankton means more steps in the food chain, possibly reducing large organism biomass more as metabolic costs outpace ingestion.
<b>Macroecological</b>	Warming drives higher individual production rates, which means fewer individuals can be supported by a given level of production, causing total biomass to decrease.	Phytoplankton size decreases with warming, lengthening food chains and reducing how much energy is transferred to higher trophic levels.	Net primary production is a key determinant of total biomass. Higher net primary production means more biomass.	Phytoplankton size decreases with decreasing production. Smaller phytoplankton support longer food chains, thus less biomass across all sizes.
<b>ZooMSS</b>	Ingestion-driven growth and mortality rates from predation and senescence scale with temperature at the same rate. Thus, temperature effects largely balance, except where senescence mortality is large, causing biomass to decrease.	Warming negatively impacts large organisms more than small by increasing senescence. If large organism biomass declines more than small, small biomass will increase from reduced predation.	The phytoplankton spectrum—set by total phytoplankton biomass—is the main food of microzooplankton. More phytoplankton means more consumer biomass.	Less phytoplankton biomass means less food for small organisms, and relatively more small phytoplankton. Drives shifts in zooplankton composition, which stabilise food chain length.

## 360 **2.4. Experimental protocol**

361 To isolate the impact of temperature and LTL processes on the FishMIP ensemble, we  
362 conducted four simulations (Table 3). In each simulation, all models were forced with  
363 different combinations of temperature, LTL and other (for APECOSM and DBEM) drivers from  
364 pre-industrial, historical and high emissions scenarios (RCP8.5; IPCC, 2014) from the CESM1-  
365 BGC earth system model (Harrison et al. 2018). All forcings were provided to modellers with  
366 a monthly temporal resolution. We do not use a range (from low to high) of emission  
367 scenarios for the future, or source forcings from multiple Earth system models, as our purpose  
368 here is to isolate sources of structural uncertainty within the FishMIP model ensemble itself  
369 (Payne et al. 2016). Under the RCP8.5 scenario, the CESM1-BGC model projects a global sea  
370 surface temperature increase, which is particularly marked at high latitudes (Figure 1b); net  
371 primary production declines across most of the tropics and mid-latitudes, but increases at  
372 high latitudes and in the eastern South Pacific (Figure 1d); phytoplankton and zooplankton  
373 biomass declines across most of the world's oceans, except in polar regions (Figure 1f, h). The  
374 mean change in sea surface temperature across the global ocean from 1950 to 2100 under  
375 historical (from 1950-2005) and RCP8.5 (from 2006-2100) scenarios is +3.2°C, and for net  
376 primary production, phytoplankton and zooplankton carbon the mean change was -14%, -8%  
377 and -21%, respectively.

378

379 To enable the model comparison, two standardized outputs - total consumer biomass and the  
380 biomass of large consumers ( $\geq 30$  cm; see Tittensor et al. 2018 for details) - were calculated  
381 from each ecosystem model. All models supplied both outputs, except DBEM which did not  
382 provide the biomass of large consumers. Outputs were reported as depth integrated carbon  
383 biomass ( $\text{g m}^{-2}$ ) and aggregated to a spatial grid with a resolution of  $1^\circ$  on a monthly or annual

384 time step, depending on model capability. Owing to differences in model formulation total  
 385 consumer biomass varies widely amongst models, all else being equal (Tittensor et al. 2018).  
 386 Since our focus was not on explaining these differences in total biomass, but rather the  
 387 differences in the responses of the models to temperature and LTL changes, we compared  
 388 model outputs using biomass change relative to biomass levels under the preindustrial  
 389 control. Further, as our focus was isolating impacts of temperature and LTL processes,  
 390 simulations were run in the absence of fishing.

391

392 Forcing data from the CESM1-BGC model used for this protocol, and all model outputs  
 393 presented here are available on the ISIMIP servers (<https://www.isimip.org/>).

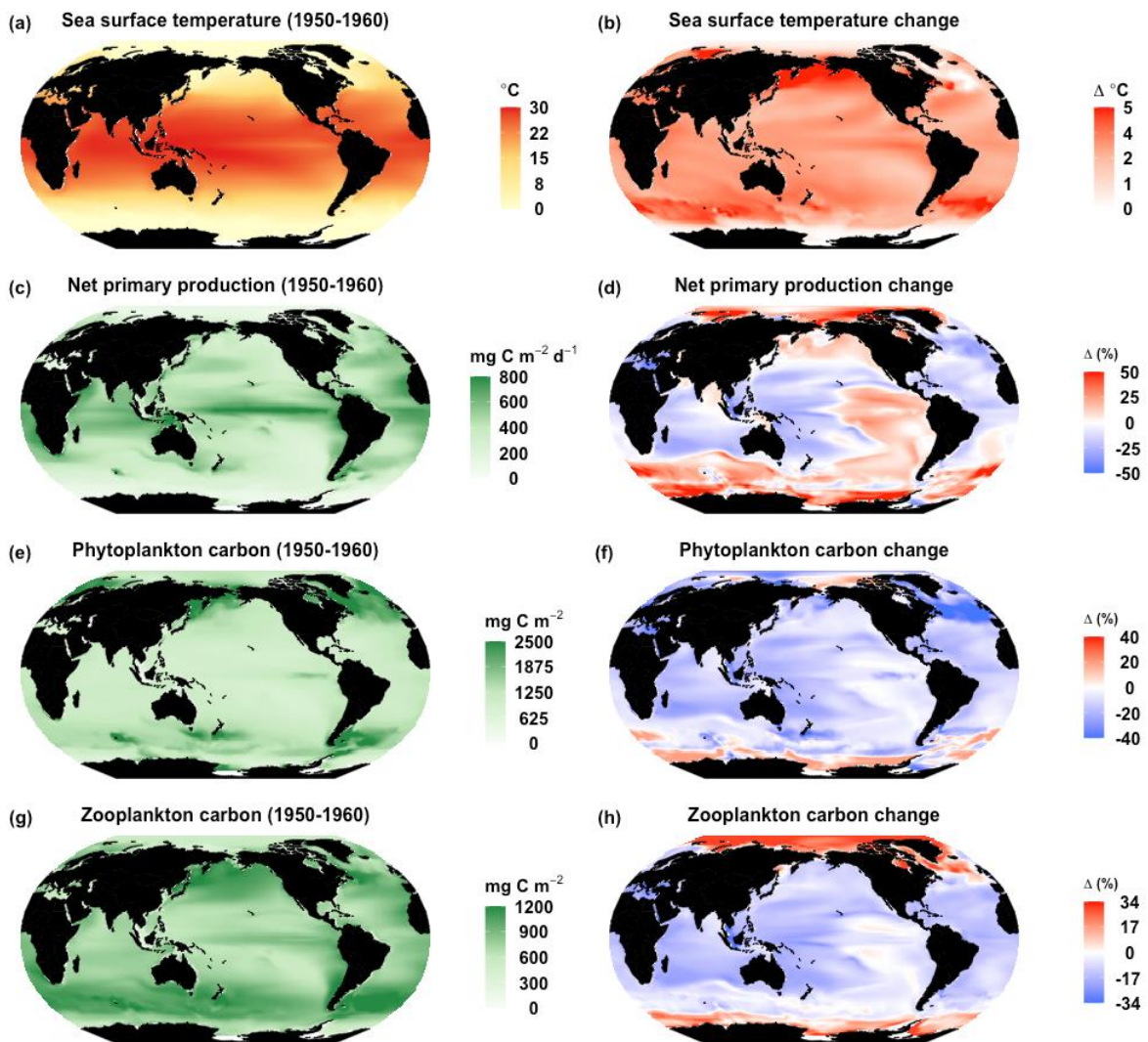
394

395 **Table 3** Summary of the experimental simulations and corresponding environmental driver  
 396 combinations. Temperature: all temperature-related drivers (e.g., sea surface temperature);  
 397 LTL: all lower trophic level drivers (e.g., phytoplankton biomass); Other: any drivers that are  
 398 not related to temperature or lower trophic levels (e.g., pH). The abbreviations for forcings  
 399 are: PI (blue) = pre-industrial control, H (yellow) = historical, RCP85 (purple) = RCP8.5.

	<u>Simulation</u>							
	Control		Temperature Change		LTL Change		All (Climate) Change	
<u>Drivers</u>	<u>1950-2005</u>	<u>2006-2100</u>	<u>1950-2005</u>	<u>2006-2100</u>	<u>1950-2005</u>	<u>2006-2100</u>	<u>1950-2005</u>	<u>2006-2100</u>
Temperature	PI	PI	H	RCP85	PI	PI	H	RCP85
LTL	PI	PI	PI	PI	H	RCP85	H	RCP85
Other	PI	PI	PI	PI	PI	PI	H	RCP85

400

401



403

404 **Figure 1** Control (historical averaged over 1950-1960) forcing variables and the change in

405 those variables from climate change (RCP8.5) from the CESM1-BGC earth system model; a,b)

406 Sea surface temperature, c,d) Net primary production, e,f) Phytoplankton carbon, g,h)

407 Zooplankton carbon. The change in each variable is measured as the mean over 2090-2100

408 under the RCP8.5 scenario minus the mean over 1950-1960 (for sea surface temperature), or

409 the percentage change between the mean in 1950-1960 and 2090-2100 (for net primary

410 production, phytoplankton carbon and zooplankton carbon).

411

412

### 413 **3. Results**

#### 414 **3.1. Global changes in total consumer biomass**

415 All models projected a decline of global consumer biomass in the Temperature Change  
416 simulation, with the exception of APECOSM (Figure 2a). The spread of total consumer biomass  
417 change in response to warming ranged from around -35% for Macroecological and BOATS, to  
418 +3% for APECOSM by the end of the 21<sup>st</sup> century. EcoTroph produced the third largest change  
419 after BOATS and Macroecological of around -13%. The remaining four models (DBEM, DBPM,  
420 FEISTY, ZooMSS) simulated modest changes in consumer biomass of between -2% (FEISTY) to  
421 -7% (DBPM) in response to changes in temperature alone.

422

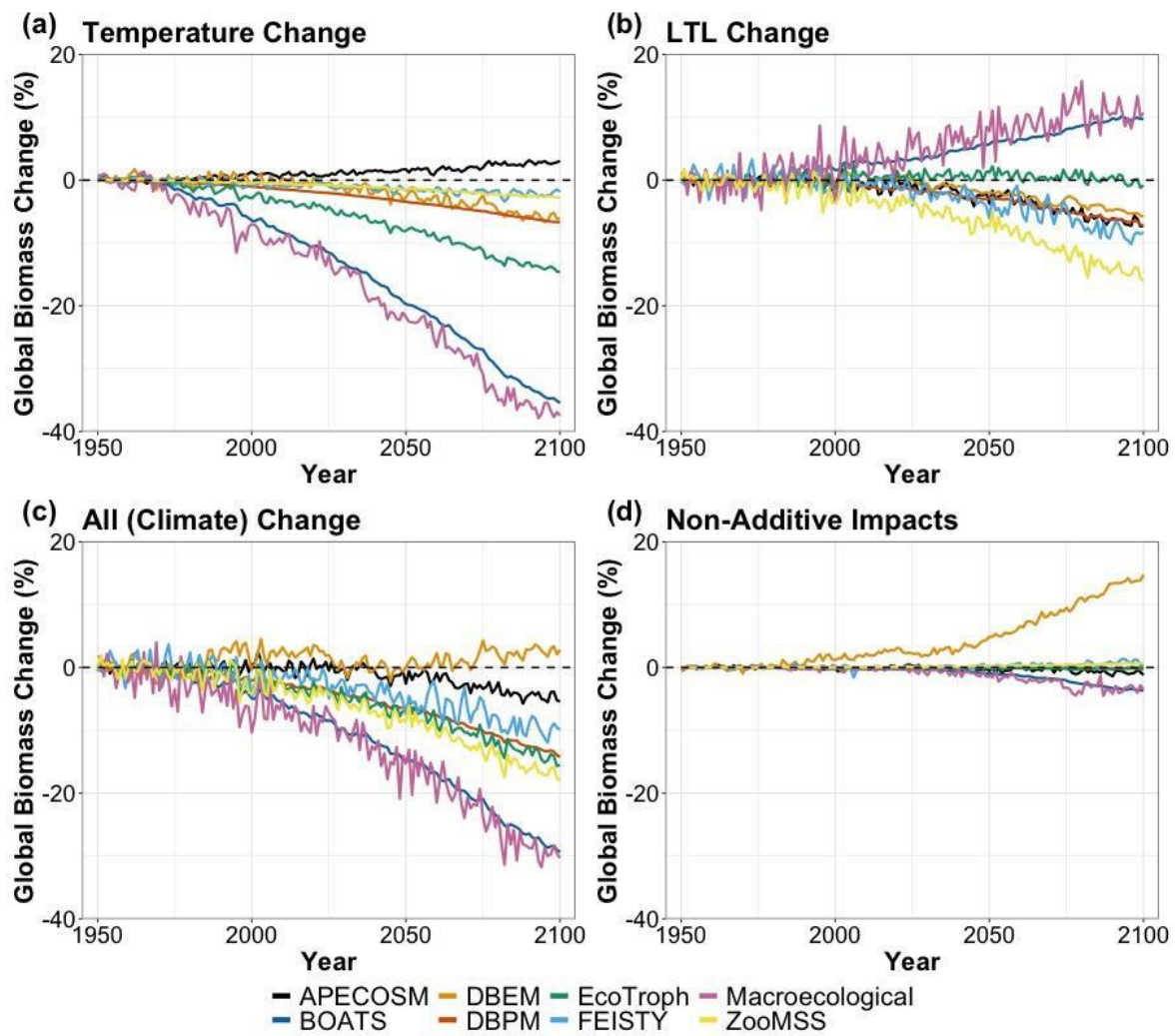
423 The LTL Change simulation also showed biomass decreases for most models, except BOATS  
424 and Macroecological, which projected biomass increases (Figure 2b). For these two models,  
425 the trajectory of biomass change was switched in the LTL Change simulation from negative  
426 change to positive in comparison with the warming only simulation. In contrast, APECOSM  
427 projected consumer biomass to increase slightly with warming, but decrease with LTL  
428 changes. APECOSM projected a 7% decrease in total consumer biomass globally, while BOATS  
429 and Macroecological projected increases of 10-15% in response to LTL changes in isolation.  
430 Maximum decreases of biomass in LTL simulations are half the magnitude (up to 15%) of the  
431 decreases in warming simulations. The smallest response to LTL changes was from EcoTroph,  
432 which projected a total consumer biomass change of <-1%. Trends in total consumer biomass  
433 from the other five models (DBEM, DBPM, FEISTY and ZooMSS) were grouped within a range  
434 between -5% (DBEM) and -15% (ZooMSS).

435

436 The combined temperature and LTL changes led to a decline in consumer biomass across all  
437 models except DBEM (Figure 2c). By the end of the 21st century, changes in consumer  
438 biomass in the All (Climate) Change simulation ranged from around -30% for BOATS and  
439 Macroecological, to +3% for DBEM. The other five models (APECOSM, DBPM, EcoTroph,  
440 FEISTY and ZooMSS) had changes in total consumer biomass of between -5% (for APECOSM)  
441 and -17% (for ZooMSS). For all models except BOATS, DBEM and Macroecological, climate  
442 change impacts at the global scale were largely the sum of the separate global impacts of  
443 warming and LTL change, with almost no non-additive impact (Figure 2d). For BOATS and  
444 Macroecological, climate change impacts caused total consumer biomass to decline by about  
445 4% more than the sum of separate warming and LTL impacts. In DBEM, total consumer  
446 biomass under climate change was ~15% higher than under the combined, separate impacts  
447 of warming and LTL impacts, indicating some non-additive impact of cumulative temperature  
448 and LTL changes. Non-additive impacts in DBEM may also be caused by additional impacts  
449 from changes in pH and oxygen levels. APECOSM, the only other model to incorporate non-  
450 temperature or LTL drivers, had negligible non-additive impacts, indicating these other drivers  
451 had little effect compared to warming and LTL shifts.

452

453



454

455 **Figure 2** Model projections of percentage change in global consumer biomass, relative to the  
 456 Control, from 1950-2100 for the: a) Temperature Change simulation, b) Lower Trophic Level  
 457 (LTL) Change simulation, c) All (Climate) Change simulation and d) the non-additive impacts  
 458 of temperature and LTL changes, calculated by taking the difference between the All Change  
 459 and the sum of the Temperature and LTL Change simulations.

460

### 461 3.2. Spatial changes in total consumer biomass

462 Globally averaged time-series of total consumer biomass change conceal considerable spatial  
 463 variation across regions, and between models in each experiment. Temperature-induced  
 464 shifts in the spatial distribution of total consumer biomass (Figure 3, left column) varied from

465 increases in many regions for APECOSM, to decreases across the global ocean in DBPM,  
466 ZooMSS, EcoTroph, BOATS and Macroecological. The magnitude of the total consumer  
467 biomass changes generally followed the magnitude of change in temperature (Figure 1b);  
468 temperate regions that experienced the strongest warming (Figure 1b) exhibited the largest  
469 decreases in biomass for these five models. FEISTY and ZooMSS consumer biomass also  
470 decreased with increased temperature in many of the regions with the greatest warming.  
471 However, in warm regions (Figure 1a) with relatively small temperature increases such as the  
472 eastern Pacific or northern Indian Ocean, FEISTY consumer biomass increased, and small  
473 increases in ZooMSS consumer biomass occurred almost entirely in very high latitude polar  
474 regions where temperature change was relatively small (Figure 1b). In contrast, APECOSM  
475 consumer biomass increased across most of the global ocean in response to warming. The  
476 exception to this pattern was in patches where phytoplankton biomass was highest (Figure  
477 1c) such as the North Atlantic, the Bering Strait or the South Pacific around New Zealand. In  
478 DBEM, temperature-induced changes in consumer biomass were greatest in the warmest  
479 waters around the equator, where DBEM consumer biomass decreased by 60-100%. In cold  
480 high latitude waters, DBEM consumer biomass increased by  $\geq 60\%$  in response to warming.

481

482 For all models, lower trophic level (LTL) induced shifts in the distribution of consumer biomass  
483 (Figure 3, centre column) show more agreement in their patterns of change; most models  
484 show biomass decreases in equatorial regions, and increases towards the poles. The  
485 exceptions here are APECOSM, FEISTY and ZooMSS which show a mix of positive and negative  
486 consumer biomass toward the north pole. Consumer biomass shifts generally followed  
487 changes in the distribution of the main LTL forcings used by each model (Figure 1d, f, h).  
488 APECOSM, DBPM, FEISTY and ZooMSS use plankton biomass inputs (Table 2), and for these

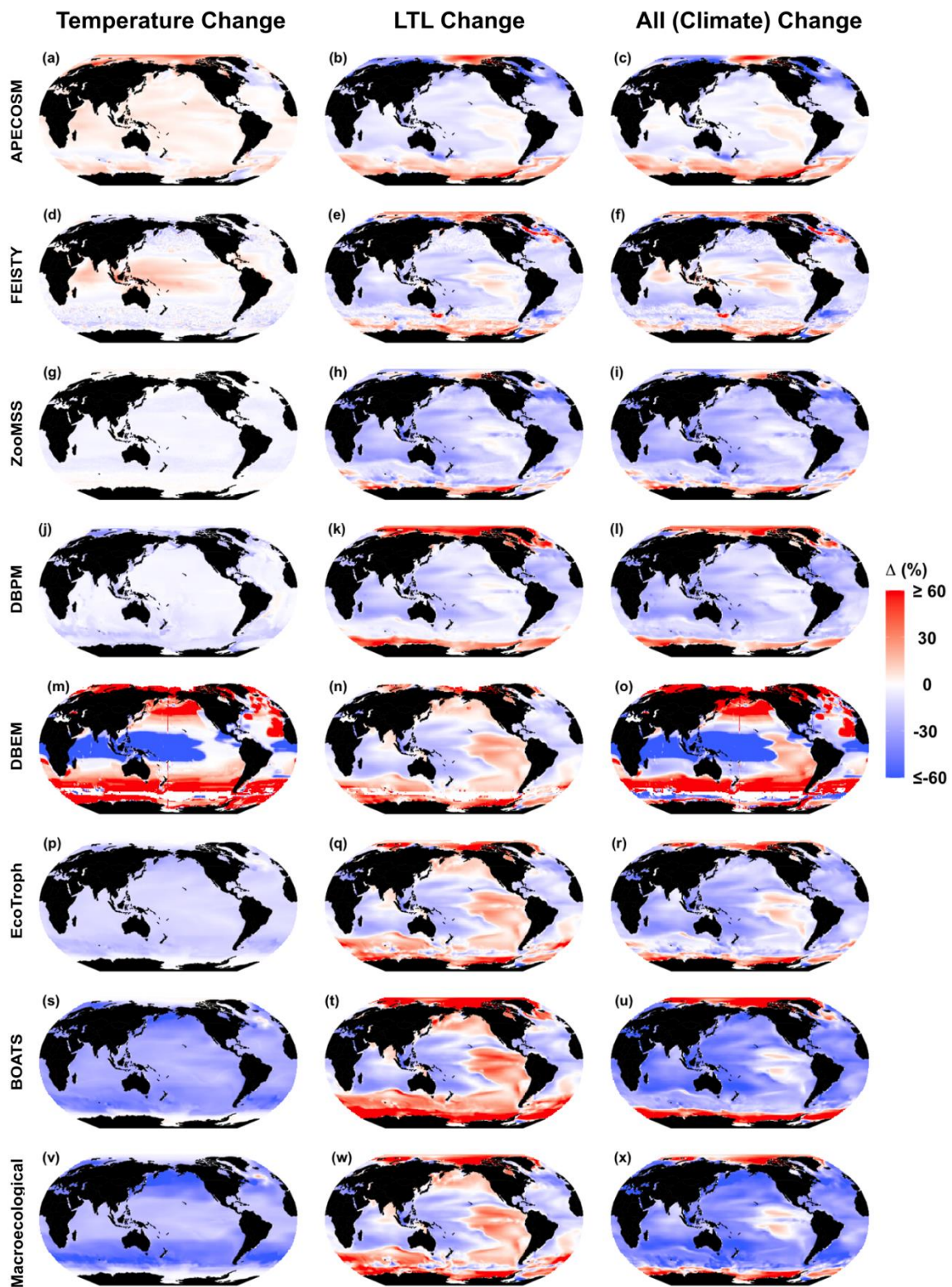


489 models, consumer biomass generally decreased with decreasing phytoplankton carbon  
490 (Figure 1f) and increases were isolated to polar regions. DBEM, EcoTroph, BOATS and  
491 Macroecological use net primary production as their LTL forcing and the spatial distribution  
492 of changes in consumer biomass followed spatial shifts in net primary production (Figure 1d),  
493 with increases in biomass not only in polar regions, but also in the North Pacific and in the  
494 south east Pacific.

495

496 When both temperature and LTL drivers changed simultaneously in the All (Climate) Change  
497 simulation, shifts in the distribution of consumer biomass for each model were a combination  
498 of the shifts driven by separate temperature and LTL effects (Figure 3, right column;  
499 Supplementary Figure S1). Across all models, temperature-induced declines in consumer  
500 biomass were generally exacerbated in regions where LTL changes negatively impacted  
501 consumer biomass. Overall, consumer biomass generally increased in polar waters, where all  
502 LTL variables increased but temperature changed relatively little. Increases in consumer  
503 biomass in DBEM were greater in polar regions under climate change, compared to the sum  
504 of the separate impacts of warming and LTL shifts (Supplementary Figure S1e). Outside of  
505 polar regions, the magnitude and direction of change in consumer biomass varied among  
506 models, depending on their individual responses to temperature and LTL changes. For BOATS  
507 and Macroecological, the magnitude of positive and negative changes in consumer biomass  
508 from LTL shifts in isolation were attenuated when combined with the impacts of warming in  
509 the Climate Change simulation (Supplementary Figure S1g, h), however these non-additive  
510 effects largely cancelled at the global scale (Figure 2d).

511



512

513 **Figure 3** Maps of relative total consumer biomass averaged over 2090-2100, compared to the  
 514 Control, for the Temperature (left column), Lower Trophic Level (LTL) and All Change

515 simulations for a-c) APECOSM, d-f) FEISTY, g-i) ZoomSS, j-l) DBPM, m-o) DBEM, p-r) EcoTroph,  
516 s-u) BOATS, v-x) Macroecological. Maps are ordered by the magnitude (from smallest to  
517 greatest) of the negative warming impact on consumer biomass.

518

### 519 **3.3. Disentangling temperature and lower trophic level impacts on total consumer** 520 **biomass**

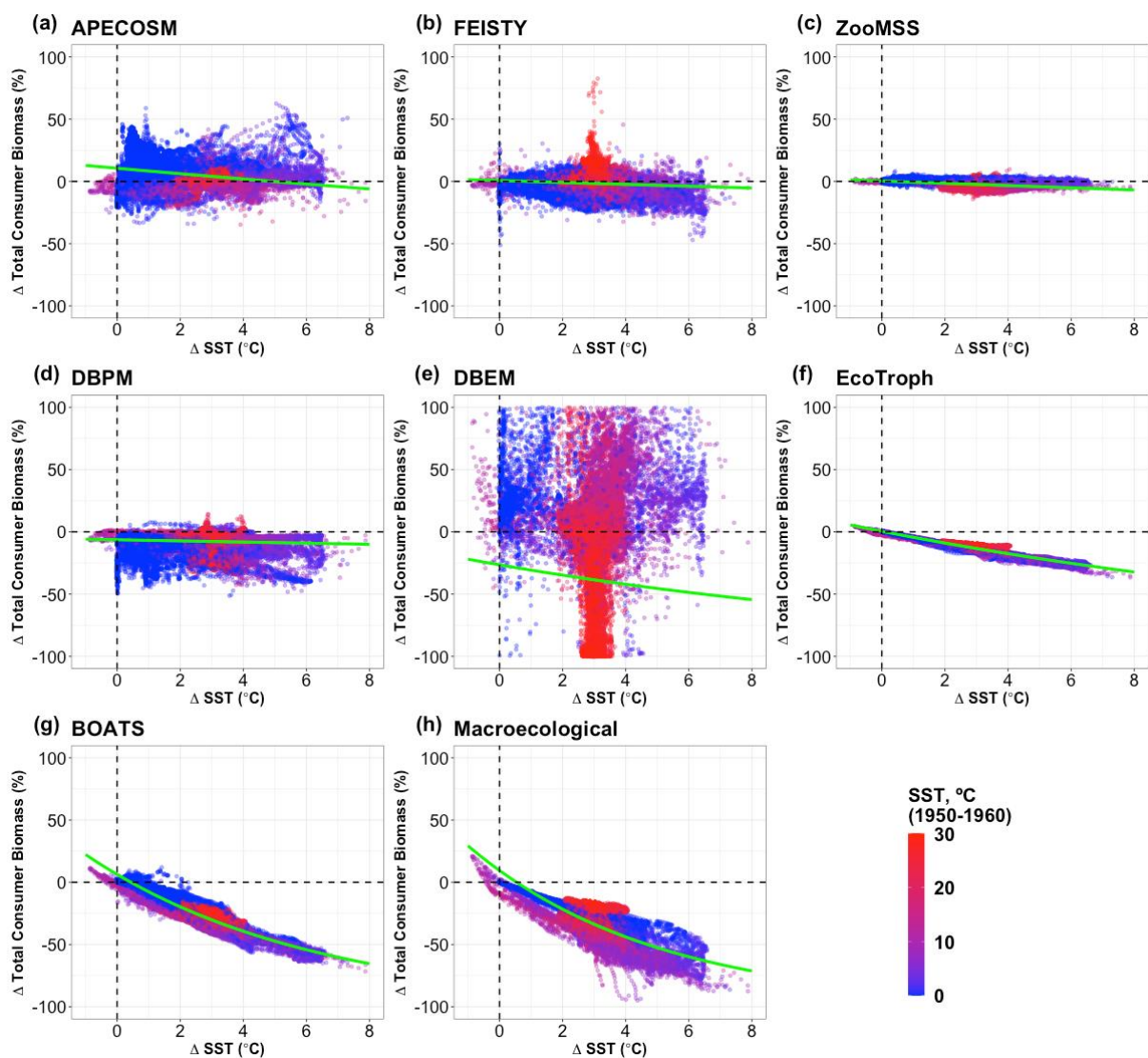
521 Figure 4 compares the forced changes in sea surface temperature with the co-located  
522 simulated changes in biomass for all grid cells in the global ocean. Regressions give negative  
523 exponential slopes for all models, but with substantial variation (Supplementary Table S1).  
524 Globally, consumer biomass changed between -0.5% and -2.0% for every 1°C of sea surface  
525 warming for APECOSM, FEISTY, DBPM and ZoomSS, and between -4.8% and -15.4% per 1°C  
526 across EcoTroph, BOATS and Macroecological (Supplementary Table S4). The models vary in  
527 their degree of linearity, with DBEM projecting the greatest nonlinearity in the impacts of  
528 warming between cold and warm waters (Figure 4e; Supplementary Table S4). DBEM  
529 consumer biomass increased by ~50% in cold waters (<15°C waters) in response to warming  
530 (Figure 4e), and decreased on average by >27% for each 1°C warming in warm ( $\geq 15^\circ\text{C}$  waters)  
531 waters.

532

533 Figure 5 shows the corresponding plots for LTL forcing. For all models, changes in total  
534 consumer biomass were positively correlated with changes in their respective aggregated  
535 lower trophic level (LTL) forcing (Figure 5). A 1% change in LTL forcings caused a change in  
536 total consumer biomass of between 0.6% in DBPM to 1.7% in BOATS (Supplementary Table  
537 S4). Positive correlations between consumer biomass and LTL changes ranged from  $r = 0.39$   
538 for DBPM, to  $r = 0.98$  for EcoTroph. For all models except DBPM, the greatest correlation

539 was between change in total consumer biomass and change in total LTL production, or  
 540 biomass, of the model's chosen LTL forcing (Supplementary Table S3). In models that used  
 541 size-fractionated LTL inputs, or additional secondary LTL inputs, changes in consumer biomass  
 542 were less correlated with changes in their main aggregated LTL forcing (APECOSM, DBPM,  
 543 FEISTY) compared to models that did not use size-fractionated or multiple LTL forcings  
 544 (BOATS, DBEM, EcoTroph, Macroecological, ZooMSS).

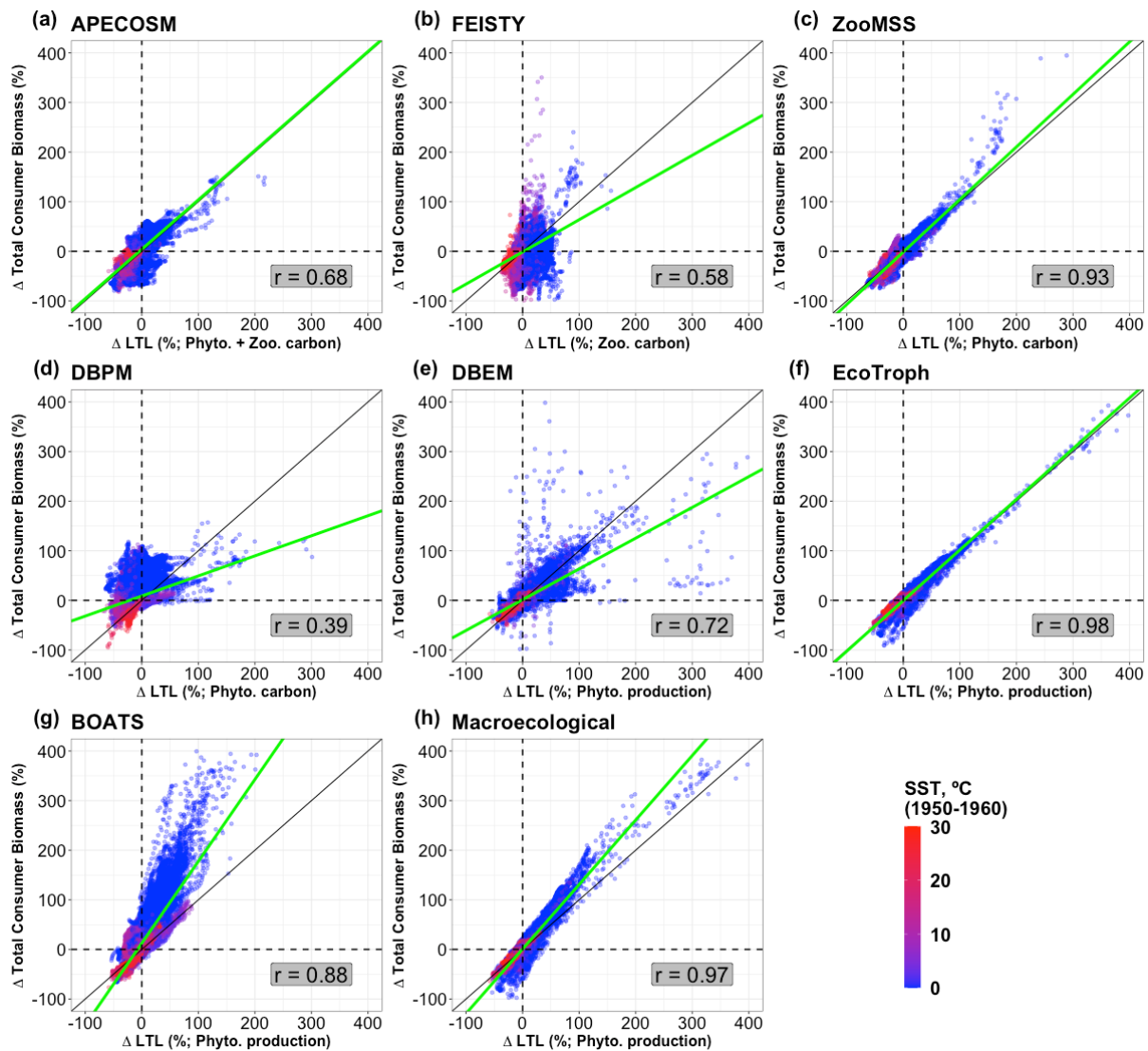
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546

547 **Figure 4** Change in total consumer biomass (%) against the mean change in sea surface  
 548 temperature (SST) over 2090-2100, for individual 1° grid squares, under the Temperature

549 Change simulation, compared to the Control simulation, for a) APECOSM, b) FEISTY, c)  
550 ZooMSS, d) DBPM, e) DBEM, f) EcoTroph, g) BOATS, h) Macroecological. Each point is coloured  
551 according to the mean 1950-1960 historical SST in its grid cell. Dotted horizontal and vertical  
552 black lines indicate where % change in total consumer biomass and change in temperature  
553 are zero, respectively. The green line is the fitted regression ( $\Delta$  Total Consumer Biomass =  
554  $\exp(\beta_0 + \beta_1 \Delta \text{SST}) + \varepsilon$ ) for the change in consumer biomass with warming. We use  
555 exponential regression to calculate the line of best fit here since all models incorporate  
556 temperature effects using an exponential function (see Supplementary Information).  
557 Information about the fitted regression is in Supplementary Table S1 and S4.  
558



559

560 **Figure 5** Change in total consumer biomass (%) against change in aggregated lower trophic  
 561 level forcings (LTL), from 2090-2100 under the LTL Change simulation, against the Control, for  
 562 individual 1° grid squares, compared to the Control simulation for a) APECOSM, b) FEISTY, c)  
 563 ZooMSS, d) DBPM, e) DBEM, f) EcoTroph, g) BOATS, h) Macroecological, with Pearson's  
 564 correlation coefficient ( $r$ ) reported for each. Each point is coloured according to the average  
 565 1950-1960 historical sea surface temperature (SST) in its corresponding grid cell. The black  
 566 solid line is the 1:1 line, and the dotted horizontal and vertical black lines indicate where %  
 567 change in total consumer biomass and % change in LTL are zero, respectively. The green line  
 568 is the fitted regression ( $\Delta$ Total Consumer Biomass =  $\beta_0 + \beta_1\Delta$ LTL +  $\epsilon$ ) for the change in

569 consumer biomass with warming. For models that use more than one LTL variable  
570 (APECOSM), or size-fractionated LTL (FEISTY and DBPM),  $\Delta$ LTL is calculated from the sum of  
571 all LTL forcings. Information about the fitted regression is in Supplementary Table S2 and S4.

572

### 573 **3.4. Impacts of warming and lower trophic level change on ecosystem structure**

574 In response to warming, there was little consensus in the relative change of small (<30 cm)  
575 and large ( $\geq$ 30 cm) consumer biomass (Figure 6a), with four models (BOATS, EcoTroph,  
576 Macroecological, ZooMSS) showing a decrease of both and the other three models  
577 (APECOSM, DBPM, FEISTY) showing a mixture of responses. Small consumer biomass  
578 increased by  $\sim$ 2% in both APECOSM and FEISTY in response to warming, but large consumer  
579 biomass increased in APECOSM by 5% while decreasing in FEISTY by  $>$ 10%. Similarly, although  
580 small consumer biomass in DBPM and ZooMSS decreased by 3% and 6% respectively, these  
581 models disagreed on the direction of change for large consumer biomass. In response to  
582 warming total large consumer biomass in DBPM increased by 15%, and even up to 60% in  
583 some regions (Supplementary Figure S2n), but ZooMSS total large consumer biomass declined  
584 by  $\sim$ 2% overall. Finally, small and large consumer biomass declined in EcoTroph, BOATS and  
585 Macroecological, and the spatial pattern of decline across these models was similar  
586 (Supplementary Figure S2). There was no difference in the magnitude of the decline of small  
587 and large consumer biomass in Macroecological, however in EcoTroph and BOATS the  
588 magnitude of the decline in large consumer biomass was greater than the decline in small  
589 consumer biomass.

590

591 Changes in total small and large consumer biomass in response to lower trophic level (LTL)  
592 changes show more agreement (Figure 6b). The change in total small and large consumer

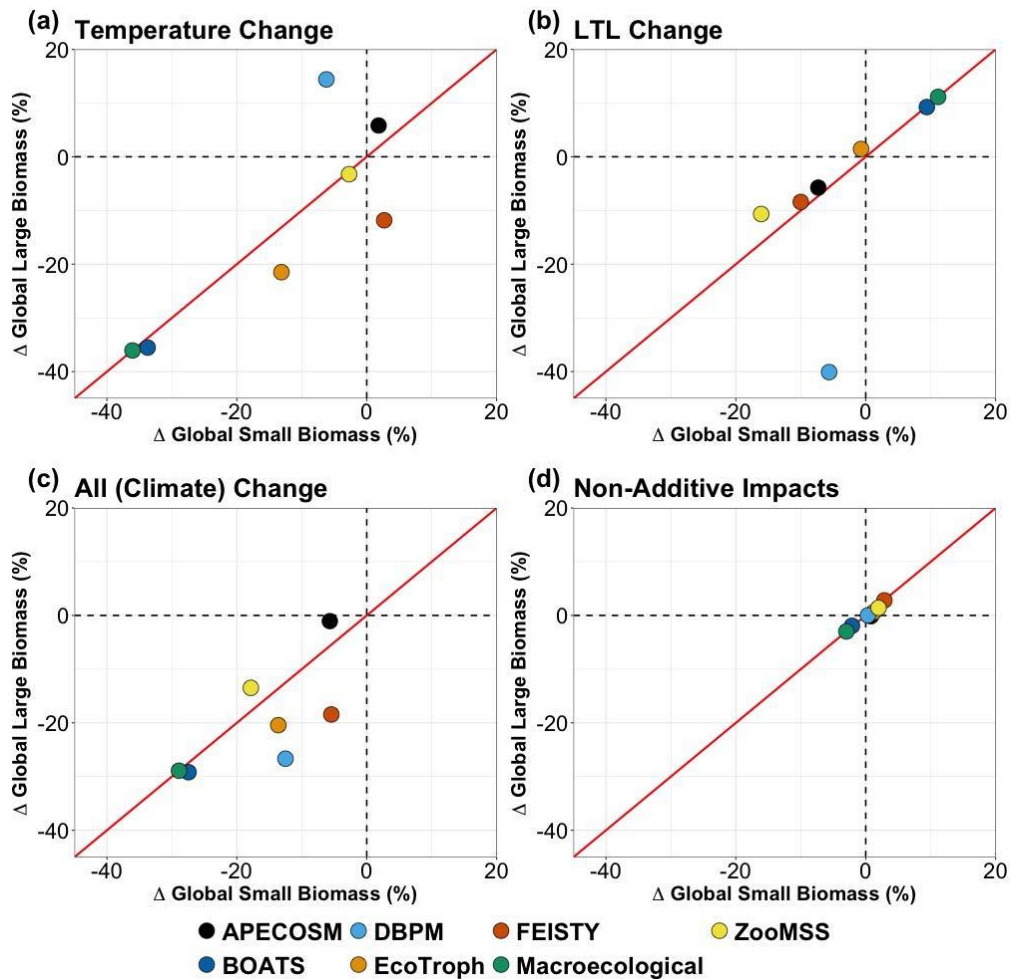
593 biomass was similar in APECOSM, FEISTY, ZooMSS, EcoTroph, BOATS and Macroecological,  
594 and again the spatial pattern of change in small and large consumer biomass generally  
595 followed each model's respective LTL forcings (Supplementary Figure S2; Figure 1f-h).  
596 However in DBPM, total large consumer biomass declined by 40%, while small consumer  
597 biomass declined by only 10%. Large consumer biomass in DBPM varied by over  $\pm 60\%$  in  
598 some regions, whereas small consumer biomass varied by  $<25\%$  across the global ocean  
599 (Supplementary Figure S2 o,p).

600

601 Small and large consumer biomass declined for all models (except DBEM, which was excluded  
602 from this part of the analysis since it did not provide size-fractionated biomass) in response  
603 to climate change (simultaneous temperature and LTL changes) impacts (Figure 6c). Large  
604 consumer biomass declined more than small consumer biomass in BOATS, DBPM, EcoTroph  
605 and FEISTY. In contrast, small consumer biomass declined more than large consumer biomass  
606 in APECOSM and ZooMSS, and there was no difference between small and large consumer  
607 biomass change in Macroecological. For all models, the impacts of climate change on small  
608 and large consumers were largely the sum of temperature and LTL impacts, with relatively  
609 small non-additive impacts (Figure 6d).

610





611

612 **Figure 6** Change in total small (<30 cm) consumer biomass versus change in global large  
 613 (>30cm) consumer biomass averaged between 2090-2100 relative to Control simulation for  
 614 each model (excluding DBEM, which did not provide small and large consumer biomass) in  
 615 the a) Temperature Change simulation b) Lower Trophic Level (LTL) Change simulation, c) All  
 616 Change simulation and d) the non-additive impacts of temperature and LTL changes,  
 617 calculated by taking the difference between the All Change and the sum of the Temperature  
 618 and LTL Change simulations. The red solid line is the 1:1 line, and the dotted horizontal and  
 619 vertical black lines indicate where the percentage change in global large and small consumer  
 620 biomass are zero, respectively.

621

622

## 623 **4. Discussion**

624 The results of our experimental protocol reveal commonalities, as well as contrasts among  
625 the FishMIP models. All models agreed that the combination of warming and lower trophic  
626 level (LTL) shifts will cause substantial regional changes in consumer biomass. Furthermore,  
627 no model projected a significant increase in global biomass in response to climate change.  
628 However, the impacts of warming varied markedly between models, leading to large inter-  
629 model disagreements. Changes in LTL drivers were more directly correlated with the  
630 outcomes on consumer biomass, but with substantial variation among models. For almost all  
631 models, the combined impacts of warming and LTL changes were largely additive at the global  
632 scale, showing little nonlinear interaction, and additional climate change drivers (e.g. oxygen,  
633 acidification, current speeds) were not significant global drivers in the models that included  
634 them (APECOSM and DBEM). By separating the marine ecosystem model responses to  
635 climate-driven warming versus LTL shifts, our results point toward the processes that need to  
636 be clarified to reduce the uncertainty of how these two dominant drivers impact marine  
637 ecosystems.

638

### 639 **4.1. Warming impacts are complex**

640 One straightforward expectation might be that the different responses to warming reflect  
641 differences in the temperature scalings used in each model. However, the differences in  
642 temperature scalings do not readily explain the variation in the results. For instance, DBPM  
643 and Macroecological use identical temperature scalings (see Supplementary Information S2.4  
644 and S2.7), yet DBPM's projections of warming-induced biomass decline are almost an order  
645 of magnitude smaller than those of Macroecological. This does not mean the temperature  
646 scalings are irrelevant, but rather that the emergent results depend on the interactions of

647 multiple temperature-dependent processes, operating within the structural context of each  
648 model.

649

650 For example, DBEM attempts to resolve preferred temperature ranges for different species,  
651 while the other models consider the effect of temperature on generalized physiological  
652 processes, implicitly assuming that species moving out of a region are replaced by species  
653 moving in with no change in ecosystem function. Although food web processes are not  
654 included in the DBEM species-distribution model, it projects an emptying of tropical waters  
655 and a corresponding build-up of biomass in polar waters, as species move poleward to follow  
656 their thermal preferences. This redistribution of the biomass of >1200 recorded commercial  
657 species included in the model reflects the absence of very warm water fish that can  
658 repopulate the tropics, and the small number of cold water fish in the initial state (Cheung et  
659 al. 2010). It also largely explains the model's combined impacts of warming, LTL shifts and  
660 other drivers being nonlinear: relative to extant species in polar waters, a larger number of  
661 species follow their thermal niche poleward and are able to take advantage of increased  
662 primary production in high latitude regions, compared to the regions they left behind.

663

664 DBEM aside, four of the models included here (APECOSM, DBPM, FEISTY and ZooMSS) project  
665 much smaller warming impacts on consumer biomass than the remaining three  
666 models (BOATS, EcoTroph and Macroecological). Although there are many differences  
667 between these models, one particularly salient feature is that the low-sensitivity models all  
668 use LTL biomass as Earth-system model (ESM) drivers for the projections, together with  
669 temperature-dependent feeding rates. In contrast, the high-sensitivity models use ESM net  
670 primary production to directly limit the growth rates of upper trophic levels. We suggest that

671 the discrepancy in temperature sensitivity between these two model groups can be  
672 attributed, at least in part, to an inconsistency that arises from the 1-way forcing of marine  
673 models with LTL biomass. The relationship between LTL biomass ( $B_{LTL}$ ), LTL production ( $P_{LTL}$ )  
674 and higher trophic level predation ( $Pred_{HTL}$ ) through time  $t$  can be represented as:

$$675 \quad \frac{dB_{LTL}}{dt} = P_{LTL}(t) - Pred_{HTL}(t).$$

676 In reality, if warming accelerates predation rates, but lower trophic level production remains  
677 constant or does not increase as much, such that  $P_{LTL}(t) < Pred_{HTL}(t)$ , LTL biomass would  
678 decrease. However in the 1-way forcing used here, LTL biomass is determined externally by  
679 the Earth system model and is not affected by predation from higher trophic levels. Thus,  
680 increased predation rates from warming on fixed LTL biomass causes an increase in the flux  
681 of biomass energy into higher trophic levels that is decoupled from lower trophic level  
682 production. This increased energy input counters the increased metabolic rates and  
683 associated respiratory losses, dampening biomass declines from warming. This inconsistency  
684 in coupling between LTLs and higher trophic level consumers would tend towards an  
685 underestimate of warming impacts on consumer biomass. In contrast, in the production-  
686 driven models there is no spurious energy input under warming, so that the respiration cost  
687 acts alone to drive biomass down strongly.

688

689 Our results also explored the warming impacts on ecosystem structure, defined as the relative  
690 biomass of small versus large organisms. Here, there was little consensus between models.  
691 DBPM and FEISTY provide a striking example of divergent projections of ecosystem structure  
692 with warming. In DBPM, ingestion-fuelled anabolism outpaces senescence-induced mortality  
693 in large organisms as waters warm (Blanchard et al. 2012), causing their biomass to increase.

694 This raises predation pressure on smaller organisms, which when coupled with warming-  
695 induced increases in natural mortality, causes their biomass to decline. By contrast, in FEISTY,  
696 biomass respiration increases faster with both body size and temperature compared to  
697 ingestion-fuelled anabolism (Petrik et al. 2019) reducing the scope for growth and causing  
698 large organism biomass to decline with warming. Declines in large consumer biomass in  
699 FEISTY with increasing temperature relieve predation pressure on small consumers, resulting  
700 in an increase in their biomass, especially in tropical waters. The divergent impacts of warming  
701 on individual processes and ecosystem structure reflects the lack of consensus among  
702 modellers of how temperature impacts on individuals translate into ecosystem impacts.

703

#### 704 **4.2. Lower trophic level impacts are influenced by choice of forcing**

705 The choice of LTL forcings differed, with each model using either biomass or production  
706 variables at the phytoplankton or zooplankton level, with significant impacts on the results.  
707 Generally, spatial changes in consumer biomass were most correlated with changes in the  
708 distribution of the LTL forcing used. The sensitivity of models to the choice of LTL forcing  
709 indicates a lack of common understanding of how to link lower trophic levels production with  
710 higher trophic levels, with no consensus on whether production rates or standing-stock  
711 biomass should be used. We believe this problem fundamentally arises out of practical  
712 necessity because of each model's one-way, offline coupling with the Earth system model—  
713 were higher trophic levels and LTLs to be fully coupled, and predation feedbacks onto the LTL  
714 resolved, there should be no disagreement on theoretical grounds. However, in the absence  
715 of two-way coupled models in the FishMIP ensemble, the development of which is a  
716 tremendous technical challenge (see Aumont et al., 2018), this problem remains to be

717 addressed. As mentioned above, this problem also leads to inconsistency in the temperature  
718 response when plankton biomass versus net primary production rates are used.

719

720 Ecosystem structure did not change substantially in response to LTL changes, except in DBPM.

721 Large organism biomass in DBPM declined by 40% and small organisms declined by <10% in

722 response to decreases in phytoplankton biomass and resultant shifts in the size structure of

723 the phytoplankton abundance spectrum. DBPM's relatively large decrease in large consumer

724 biomass in response to phytoplankton biomass declines is a result of biomass destruction

725 through senescence mortality, which increases with body size but does not depend on food

726 density, outpacing ingestion-fuelled biomass creation. The other predation-explicit models—

727 including ZoomSS and FEISTY, which also include biomass destruction processes independent

728 of food density that increase with body size—did not exhibit similar declines in large organism

729 biomass. This is because in these models, ingestion-fuelled growth outpaces biomass

730 destruction from these processes, highlighting the sensitivity of model outputs to the

731 parameterisation of these rates. In fact, across all models except DBPM, the change in large

732 organism biomass with LTL change was equal to or slightly less than the change in small

733 organism biomass.

734

#### 735 **4.3. Cumulative warming and lower trophic level impacts are largely additive**

736 Across the model ensemble, climate change impacts on total consumer biomass and

737 ecosystem structure were generally well-approximated by the sum of separate warming and

738 LTL impacts. This lack of non-linearity is perhaps less surprising for the majority of models that

739 only use temperature and LTL drivers to force their models (Tittensor et al. 2018), but

740 remarkably it also holds for APECOSM, which incorporates other drivers such as oxygen, pH

741 and current velocity. The fact that the overall climate change impact on consumer biomass in  
742 APECOSM was close to the sum of temperature and LTL impacts indicates that the additional  
743 forcings have a comparatively small effect. DBEM, which also includes additional  
744 environmental drivers, did show a much stronger non-additive impact of climate change on  
745 overall consumer biomass, but this appeared to be driven primarily by the relocation of  
746 species niches in DBEM in response to warming, rather than the other drivers. DBEM aside,  
747 only BOATS and Macroecological show significant non-linear interactions between  
748 temperature and LTL drivers. This can be attributed to the fact that, in BOATS and  
749 Macroecological, the representative size of phytoplankton used to force the models scales  
750 with both net primary production and temperature, increasing in cooler waters or regions  
751 with high net primary production (Dunne et al. 2005). For these two models, the spatial  
752 pattern of attenuation follows shifts in net primary production, indicating that warming  
753 attenuates the increases and decreases in biomass from shifts in net primary production.

754

755 It may be tempting to assume that the lack of nonlinear interactions in the models means that  
756 such nonlinearities are unlikely to exist in the ocean. However, an increasing number of  
757 experimental and observational studies indicate that cumulative impacts from climate change  
758 stressors such as warming, deoxygenation and acidification are likely to be nonlinear and  
759 amplifying (Sampaio and Rosa, 2020). Rather, given the rudimentary representation of many  
760 ecosystem processes in the models (e.g. no phenological or diversity-related mechanisms,  
761 simplistic or absent predation relationships), we suggest that it is more appropriate to ascribe  
762 the lack of nonlinear interactions in marine climate change projections to our present lack of  
763 ability to resolve them in the models.

764

#### 765 **4.4. Improving marine ecosystem models with observational constraints**

766 In this study, we have identified key sources of structural uncertainty that drive disparate  
767 projections of climate change impacts on the global marine ecosystem. As a first step, the  
768 marine modelling community can work to reduce this structural uncertainty and increase the  
769 credibility of ecosystem projections by constraining models with independent observations.  
770 An increasingly popular approach to confront model projections with observations is to use  
771 emergent constraints, which relate the long-term climate sensitivity of an observable  
772 ecosystem feature - such as total biomass change (Free et al. 2019) or size-spectrum slope  
773 (Blanchard et al. 2017; Heneghan et al. 2019) - to its short-term, observed variability (Allen &  
774 Ingram, 2002; Eyring et al. 2019). Models that give a closer fit to short-term observed  
775 variability of an ecosystem feature are hypothesised to provide more reliable projections of  
776 its long-term variability from climate change (Kwiatkowski et al. 2017; Veytia et al. 2020).  
777 Moreover, within a model ensemble, each model's weighting can be linked to its ability to  
778 capture the emergent constraint (Eyring et al. 2019). This provides a more sophisticated and  
779 credible way to weight model projections within an ensemble, over the standard approach  
780 where all models are given equal weighting (known as model democracy), irrespective of  
781 performance (Knutti, 2010). Emergent constraints do not require or necessarily reward any  
782 particular ecosystem representation. This is important as differing representations of the  
783 marine ecosystem across the FishMIP ensemble not only represent our present uncertainty  
784 of the most important drivers structuring marine ecosystems, but also the diversity of  
785 purpose and scope for which models have been built.

786

787 Finally, it is possible for models to perform well against whole-ecosystem emergent  
788 constraints, while neglecting fundamental physiological or ecosystem processes (Knutti,



789 2010). Therefore, if we are to improve marine models, it is also necessary to consider  
790 observational constraints on physiological processes such as the balance between growth and  
791 respiration with temperature, or ecosystem processes such as the coupling of lower and  
792 higher trophic levels. Improving our understanding of how physiological processes such as  
793 ingestion and metabolism respond to warming, and how changes in LTL processes propagate  
794 through marine ecosystems, are critical steps towards model improvement and more robust  
795 climate impact projections.

796

## 797 **5. Concluding remarks**

798 Projecting the global impact of climate change on marine ecosystems and fisheries is an  
799 important and challenging task. Marine ecosystem models represent the current  
800 understanding of how climate change could impact the food web and fisheries globally in the  
801 future. Yet, although these models have made great strides in recent years, our results show  
802 that the current understanding falls short in many respects.

803

804 Our harmonized experimental protocol clearly showed that the responses to the two most  
805 important drivers of change – warming and LTL shifts – differ widely among models.  
806 Uncertainty in the temperature sensitivities of competing processes, including both  
807 physiology and ecological interactions, undermine confidence in the emergent sensitivities,  
808 and can only be improved with better observational constraints. Meanwhile, the outcome of  
809 changes in both water temperature and LTL production depend strongly on the feedback of  
810 consumers on the LTL biomass itself, a process which is not captured by any of the one-way  
811 forcings available at present, and can only be rectified with fully two-way coupling, which is  
812 itself sure to raise many new questions.

813

814 What are the implications of our results for single ecosystem model studies? The eight models  
815 used here differ significantly in their design and ecosystem representation, having been built  
816 for different purposes (Tittensor et al. 2018). Although using common outputs across models  
817 has been useful here to identify shared weaknesses, this approach conceals the strengths of  
818 individual models to resolve certain processes and ecosystem components that other models  
819 do not. Thus, studies that explore the unique strengths and weaknesses of individual models  
820 remain important, to explore questions that each model has been designed to address.  
821 However, results of these single model studies should be interpreted within the greater  
822 context of sources of structural uncertainty shared across models, which have been identified  
823 here.

824

825 Attempting to summarise the vast complexity of the global marine ecosystem in a handful of  
826 equations is enormously difficult. The fact that independently-constructed models with  
827 contrasting architectures have arrived at many similar conclusions is encouraging, while their  
828 diversity is useful to identify common weaknesses. These initial results from the FishMIP  
829 ensemble provide a glimpse into the great promise of multi-model comparisons to improve  
830 our understanding of the global marine ecosystem and its future under change.

831

### 832 **Code and data availability**

833 The experimental protocol is described in this paper but has not code associated with it.  
834 Forcing data from CMIP5 used for the protocol, and the FishMIP model outputs presented in  
835 this paper are available on the ISIMIP servers ([https://www.isimip.org/gettingstarted/#how-](https://www.isimip.org/gettingstarted/#how-to-join-isimip)  
836 [to-join-isimip](https://www.isimip.org/gettingstarted/#how-to-join-isimip)).

837 **Author contributions**

838 JLB, TDE, EDG and DPT led the conceptualisation and development of the protocol for this  
839 study, with contributions from the other authors. CH and RFH obtained and processed  
840 forcings for the modellers to complete the protocol, with assistance from JV. Model  
841 simulations were conducted by RFH, NB, CB, WC, MC, TDE, ME, JAG, DF, JG, OM, JP, CMP,  
842 HdP, JS, TCT, PAW. RFH conducted the analysis, with assistance from EDG and JLB. RFH led  
843 the writing of the text, with feedback and contributions from all authors.

844

845 **Competing interests**

846 The authors declare that they have no conflict of interest.

847

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861 **References**

862 Allen, M. R., & Ingram, W. J. (2002). Constraints on future changes in climate and the  
863 hydrologic cycle. *Nature*, 419(6903), 228–232. <https://doi.org/10.1038/nature01092>

864 Aumont, O., Maury, O., Lefort, S., & Bopp, L. (2018). Evaluating the potential impacts of the  
865 diurnal vertical migration by marine organisms on marine biogeochemistry. *Global*  
866 *Biogeochemical Cycles*, 32, 1622-1643. <https://doi.org/10.1029/2018GB005886>

867 Barange, M., Merino, G., Blanchard, J. L., Scholtens, J., Harle, J., Allison, E. H., ... Jennings, S.  
868 (2014). Impacts of climate change on marine ecosystem production in societies dependent  
869 on fisheries. *Nature Climate Change*, 4, 211. Retrieved from  
870 <https://doi.org/10.1038/nclimate2119>

871 Barnes, C., Irigoien, X., De Oliveira, J. A. A., Maxwell, D., & Jennings, S. (2011). Predicting  
872 marine phytoplankton community size structure from empirical relationships with remotely  
873 sensed variables. *Journal of Plankton Research*, 33(1), 13–24.  
874 <https://doi.org/10.1093/plankt/fbq088>

875 Blanchard, J. L., Heneghan, R. F., Everett, J. D., Trebilco, R., & Richardson, A. J. (2017b). From  
876 Bacteria to Whales: Using Functional Size Spectra to Model Marine Ecosystems. *Trends in*  
877 *Ecology and Evolution*, 32(3), 174–186. <https://doi.org/10.1016/j.tree.2016.12.003>

878 Blanchard, J. L., Jennings, S., Holmes, R., Harle, J., Merino, G., Allen, J. I., ... Barange, M. (2012).  
879 Potential consequences of climate change for primary production and fish production in large  
880 marine ecosystems. *Philosophical Transactions of the Royal Society B: Biological Sciences*,  
881 367(1605), 2979–2989. <https://doi.org/10.1098/rstb.2012.0231>

882 Blanchard, J. L., Jennings, S., Law, R., Castle, M. D., McCloghrie, P., Rochet, M. J., & Benoît, E.  
883 (2009). How does abundance scale with body size in coupled size-structured food webs?  
884 *Journal of Animal Ecology*, 78(1), 270–280. [https://doi.org/10.1111/j.1365-](https://doi.org/10.1111/j.1365-2656.2008.01466.x)  
885 2656.2008.01466.x

886 Blanchard, J. L., Watson, R. A., Fulton, E. A., Cottrell, R. S., Nash, K. L., Bryndum-Buchholz, A.,  
887 ... Müller, C. (2017a). Linked sustainability challenges and trade-offs among fisheries,  
888 aquaculture and agriculture. *Nature Ecology & Evolution*, 1, 1240–1249.  
889 <https://doi.org/10.1038/s41559-017-0258-8>

890 Boyce, D. G., Frank, K. T., & Leggett, W. C. (2015). From mice to elephants: overturning the  
891 ‘one size fits all’ paradigm in marine plankton food chains. *Ecology Letters*, 18(6), 504–515.  
892 <https://doi.org/10.1111/ele.12434>

893 Boyce, D. G., Lotze, H. K., Tittensor, D. P., Carozza, D. A., & Worm, B. (2020). Future ocean  
894 biomass losses may widen socioeconomic equity gaps. *Nature Communications*, 1–11.  
895 Retrieved from <https://doi.org/10.1038/s41467-020-15708-9>

896 Brander, K., Neuheimer, A., Andersen, K. H., & Hartvig, M. (2013). Overconfidence in model  
897 projections. *ICES Journal of Marine Science*, 70, 1065–1068.

898 Brito-Morales, I., Schoeman, D. S., Molinos, J. G., Burrows, M. T., Klein, C. J., Arafteh-dalmau,  
899 N., ... Garilao, C. (2020). Climate velocity reveals increasing exposure of deep-ocean  
900 biodiversity to future warming. *Nature Climate Change*, 10(June), 576–581.  
901 <https://doi.org/10.1038/s41558-020-0773-5>

902 Brown, J. H., Gillooly, J. F., Allen, A. P., Savage, V. M., & West, G. B. (2004). Toward a metabolic  
903 theory of ecology. *Ecology*, *85*(7), 1771–1789. <https://doi.org/10.1890/03-9000>

904 Bryndum-Buchholz, A., Prentice, F., Tittensor, D. P., Blanchard, J. L., Cheung, W. W. L.,  
905 Christensen, V., ... Lotze, H. K. (2020). Differing marine animal biomass shifts under 21st  
906 century climate change between Canada's three oceans. *Facets*, (5), 105–122.  
907 <https://doi.org/10.1139/facets-2019-0035>

908 Carozza, D. A., Bianchi, D., & Galbraith, E. D. (2016). The ecological module of BOATS-1.0: a  
909 bioenergetically constrained model of marine upper trophic levels suitable for studies of  
910 fisheries and ocean biogeochemistry. *Geosci. Model Dev.*, *9*(4), 1545–1565.  
911 <https://doi.org/10.5194/gmd-9-1545-2016>

912 Carozza, D. A., Bianchi, D., & Galbraith, E. D. (2017). Formulation , General Features and Global  
913 Calibration of a Bioenergetically-Constrained Fishery Model. *Plos One*, *12*(1), e0169763.  
914 <https://doi.org/10.1371/journal.pone.0169763>

915 Carozza, D. A., Bianchi, D., & Galbraith, E. D. (2018). Metabolic impacts of climate change on  
916 marine ecosystems: Implications for fish communities and fisheries. *Global Ecology and*  
917 *Biogeography*, *28*, 158–169. <https://doi.org/10.1111/geb.12832>

918 Chavez, F. P., Messi, M., & Pennington, J. T. (2011). Marine Primary Production in Relation to  
919 Climate Variability and Change. *Annual Review of Marine Science*, *3*, 227–260.  
920 <https://doi.org/10.1146/annurev.marine.010908.163917>

921 Cheung, W. W. L., Dunne, J., Sarmiento, J. L., & Pauly, D. (2011). Integrating ecophysiology  
922 and plankton dynamics into projected maximum fisheries catch potential under climate

923 change in the Northeast Atlantic. *ICES Journal of Marine Science*, 68(6), 1008–1018.  
924 <https://doi.org/10.1093/icesjms/fsr012>

925 Cheung, W. W. L., Frolicher, T. L., Asch, R. G., Jones, M. C., Pinsky, M. L., Reygondeau, G., ...  
926 Watson, J. R. (2016). Building confidence in projections of the responses of living marine  
927 resources to climate change. *ICES Journal of Marine Science*, 73, 1283–1296.

928 Cheung, W. W. L., Lam, V. W. Y., & Pauly, D. (2008). Modelling Present and Climate-Shifted  
929 Distribution of Marine Fishes and Invertebrates. *Fisheries Centre Research Reports*, 16(3), 76.  
930 <https://doi.org/papers3://publication/uuid/4F260971-0169-4716-AFAA-5F970130A95C>

931 Cheung, W. W. L., Lam, V. W. Y., Sarmiento, J. L., Kearney, K., Watson, R., Zeller, D., & Pauly,  
932 D. (2010). Large-scale redistribution of maximum fisheries catch potential in the global ocean  
933 under climate change. *Global Change Biology*, 16(1), 24–35. [https://doi.org/10.1111/j.1365-](https://doi.org/10.1111/j.1365-2486.2009.01995.x)  
934 [2486.2009.01995.x](https://doi.org/10.1111/j.1365-2486.2009.01995.x)

935 Coll, M., Steenbeek, J., Pennino, M. G., Buszowski, J., Kaschner, K., Lotze, H. K., ... Christensen,  
936 V. (2020). Advancing Global Ecological Modeling Capabilities to Simulate Future Trajectories  
937 of Change in Marine Ecosystems. *Frontiers in Marine Science*, 7, 1–23.  
938 <https://doi.org/10.3389/fmars.2020.567877>

939 du Pontavice, H., Gascuel, D., Reygondeau, G., Maureaud, A., & Cheung, W. W. L. (2020).  
940 Climate change undermines the global functioning of marine food webs. *Global Change*  
941 *Biology*, 26(3), 1306–1318. <https://doi.org/10.1111/gcb.14944>

942 Dunne, J. P., Armstrong, R. A., Gnanadesikan, A., & Sarmiento, J. L. (2005). Empirical and  
943 mechanistic models for the particle export ratio. *Global Biogeochemical Cycles*,  
944 19(December), 1–16. <https://doi.org/10.1029/2004GB002390>

945 Eddy, T. D., Bernhardt, J. R., Blanchard, J. L., Cheung, W. W. L., Colléter, M., Pontavice, H., ...  
946 Watson, R. A. (2020). Trends in Ecology & Evolution Energy Flow Through Marine Ecosystems :  
947 Confronting Transfer Efficiency. *Trends in Ecology & Evolution*, xx(xx), 1–11. Retrieved from  
948 <https://doi.org/10.1016/j.tree.2020.09.006>

949 Eyring, V., Cox, P. M., Flato, G. M., Gleckler, P. J., Abramowitz, G., Caldwell, P., ... Williamson,  
950 M. S. (2019). Taking climate model evaluation to the next level. *Nature Climate Change*, 9(2),  
951 102–110. <https://doi.org/10.1038/s41558-018-0355-y>

952 Finkel, Z. V., Beardall, J., Flynn, K. J., Quigg, A., Rees, T. A. V., & Raven, J. A. (2010).  
953 Phytoplankton in a changing world: Cell size and elemental stoichiometry. *Journal of Plankton*  
954 *Research*, 32(1), 119–137. <https://doi.org/10.1093/plankt/fbp098>

955 Free, C. M., Thorson, J. T., Pinsky, M. L., Oken, K. L., Wiedenmann, J., & Jensen, O. P. (2019).  
956 Impacts of historical warming on marine fisheries production. *Science*, 363(March), 979–983.  
957 <https://doi.org/10.1126/science.aau1758>

958 Gascuel, D., & Pauly, D. (2009). EcoTroph : Modelling marine ecosystem functioning and  
959 impact of fishing. *Ecological Modelling*, 220, 2885–2898.  
960 <https://doi.org/10.1016/j.ecolmodel.2009.07.031>

961 Harrison, C. S., Long, M. C., Lovenduski, N. S. and Moore, J. K. (2018). Mesoscale Effects on  
962 Carbon Export: A Global Perspective, *Global Biogeochem. Cycles*, 32(4), 680–703,  
963 doi:10.1002/2017GB005751, 2018.



964

965 Heneghan, R. F., Everett, J. D., Blanchard, J. L., & Richardson, A. J. (2016). Zooplankton Are  
966 Not Fish: Improving Zooplankton Realism in Size-Spectrum Models Mediates Energy Transfer  
967 in Food Webs. *Frontiers in Marine Science*, 3(October), 1–15.  
968 <https://doi.org/10.3389/fmars.2016.00201>

969 Heneghan, R. F., Everett, J. D., Sykes, P., Batten, S. D., Edwards, M., Takahashi, K., ...  
970 Richardson, A. J. (2020). A functional size-spectrum model of the global marine ecosystem  
971 that resolves zooplankton composition. *Ecological Modelling*, 435(August), 109265.  
972 <https://doi.org/10.1016/j.ecolmodel.2020.109265>

973 Heneghan, R. F., Hatton, I. A., & Galbraith, E. D. (2019). Climate change impacts on marine  
974 ecosystems through the lens of the size spectrum. *Emerging Topics in Life Sciences*, 3(2), 233-  
975 243. <https://doi.org/10.0142/etls20190042>

976 IPCC, 2014: *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and*  
977 *III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core  
978 Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

979 Jennings, S., & Collingridge, K. (2015). Predicting consumer biomass, size-structure,  
980 production, catch potential, responses to fishing and associated uncertainties in the world's  
981 marine ecosystems. *PLoS ONE*, 10(7), e0133794.  
982 <https://doi.org/10.1371/journal.pone.0133794>

983 Jones, M. C., Dye, S. R., Pinnegar, J. K., Warren, R., & Cheung, W. W. L. (2012). Modelling  
984 commercial fish distributions: Prediction and assessment using different approaches.  
985 *Ecological Modelling*, 225, 133–145. <https://doi.org/10.1016/j.ecolmodel.2011.11.003>

986 Knutti, R. (2010). The end of model democracy ? : An editorial comment. *Climatic Change*, 102,  
987 395–404. <https://doi.org/10.1007/s10584-010-9800-2>

988 Kooijman, S. (2010). *Dynamic Energy Budget theory for metabolic organisation* (3<sup>rd</sup> ed.).  
989 Cambridge: Cambridge University Press.

990 Kwiatkowski, L., Bopp, L., Aumont, O., Ciais, P., Cox, P. M., Laufkötter, C., ... Séférian, R. (2017).  
991 Emergent constraints on projections of declining primary production in the tropical oceans.  
992 *Nature Climate Change*, 7(April), 355–359. <https://doi.org/10.1038/NCLIMATE3265>

993 Lefevre, S., McKenzie, D. J., & Nilsson, G. E. (2017). Models projecting the fate of fish  
994 populations under climate change need to be based on valid physiological mechanisms.

995 Lotze, H. K., Tittensor, D. P., Bryndum-Buchholz, A., Eddy, T. D., Cheung, W. W. L., Galbraith,  
996 E. D., ... Worm, B. (2019). Global ensemble projections reveal trophic amplification of ocean  
997 biomass declines with climate change. *Proceedings of the National Academy of Sciences of*  
998 *the United States of America*, 116(26), 12907–12912.  
999 <https://doi.org/10.1073/pnas.1900194116>

1000 Maury, O. (2010). An overview of APECOSM, a spatialized mass balanced “Apex Predators  
1001 ECOSystem Model” to study physiologically structured tuna population dynamics in their  
1002 ecosystem. *Progress in Oceanography*, 84(1–2), 113–117.  
1003 <https://doi.org/10.1016/j.pocean.2009.09.013>

1004 Maury, O., Faugeras, B., Shin, Y. J., Poggiale, J. C., Ari, T. Ben, & Marsac, F. (2007a). Modeling  
1005 environmental effects on the size-structured energy flow through marine ecosystems. Part 1:

1006 The model. *Progress in Oceanography*, 74(4), 479–499.  
1007 <https://doi.org/10.1016/j.pocean.2007.05.002>

1008 Maury O., J.-C. Poggiale, 2013. From individuals to populations to communities: a Dynamic  
1009 Energy Budget model of marine ecosystem size-spectrum including life history diversity.  
1010 *Journal of Theoretical Biology*. 324, 52–71. <https://doi.org/10.1016/j.jtbi.2013.01.018>

1011 Maury, O., Shin, Y. J., Faugeras, B., Ari, T. Ben, & Marsac, F. (2007b). Modeling environmental  
1012 effects on the size-structured energy flow through marine ecosystems. Part 2: Simulations.  
1013 *Progress in Oceanography*, 74(4), 500–514.  
1014 <https://doi.org/doi:10.1016/j.pocean.2007.05.001>

1015 Payne, M. R., Barange, M., Cheung, W. W. L., Mackenzie, B. R., Batchelder, H. P., Cormon, X.,  
1016 ... Queiro, A. M. (2016). Uncertainties in projecting climate-change impacts in marine  
1017 ecosystems. *ICES Journal of Marine Science*, 73(5), 1272–1282.  
1018 <https://doi.org/doi:10.1093/icesjms/fsv231>

1019 Petrik, C. M., Stock, C. A., Andersen, K. H., van Denderen, P. D., & Watson, J. R. (2019). Bottom-  
1020 up drivers of global patterns of demersal, forage, and pelagic fishes. *Progress in*  
1021 *Oceanography*, 176, 102124. <https://doi.org/https://doi.org/10.1016/j.pocean.2019.102124>

1022 Pinsky, M. L., Selden, R. L., & Kitchel, Z. J. (2020). Climate-Driven Shifts in Marine Species  
1023 Ranges: Scaling from Organisms to Communities. *Annual Review of Marine Science*, 12, 153–  
1024 179. <https://doi.org/10.1146/annurev-marine-010419-010916>

1025 Poloczanska, E. S., Burrows, M. T., Brown, C. J., Molinos, J. G., Halpern, B. S., Hoegh-Guldberg,  
1026 O., ... Sydeman, W. J. (2016). Responses of marine organisms to climate change across oceans.  
1027 *Frontiers in Marine Science*, 3(MAY), 1–21. <https://doi.org/10.3389/fmars.2016.00062>

1028 Pörtner, H.-O., D.M. Karl, P.W. Boyd, W.W.L. Cheung, S.E. Lluch-Cota, Y. Nojiri, D.N. Schmidt,  
1029 and P.O. Zavialov, 2014: Ocean systems. In: *Climate Change 2014: Impacts, Adaptation, and*  
1030 *Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth*  
1031 *Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C.B., V.R. Barros,  
1032 D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C.  
1033 Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White  
1034 (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp.  
1035 411-484.

1036 Ryther, J. H. (1969). Photosynthesis and Fish Production in the Sea. *Science*, 166(3901), 72 LP  
1037 – 76. <https://doi.org/10.1126/science.166.3901.72>

1038 Sampaio E., Rosa R. (2020) Climate Change, Multiple Stressors, and Responses of Marine  
1039 Biota. In: Leal Filho W., Azul A.M., Brandli L., Özuyar P.G., Wall T. (eds) Climate Action.  
1040 Encyclopedia of the UN Sustainable Development Goals. Springer, Cham.  
1041 [https://doi.org/10.1007/978-3-319-95885-9\\_90](https://doi.org/10.1007/978-3-319-95885-9_90)

1042 Stock, Charles A., John, J. G., Rykaczewski, R. R., Asch, R. G., Cheung, W. W. L., Dunne, J. P., ...  
1043 Watson, R. A. (2017). Reconciling fisheries catch and ocean productivity. *Proceedings of the*  
1044 *National Academy of Sciences*, 114(8), E1441–E1449.  
1045 <https://doi.org/10.1073/pnas.1610238114>

1046 Tittensor, D. P., Eddy, T. D., Lotze, H. K., Galbraith, E. D., Cheung, W. W. L., Barange, M., ...  
1047 Bryndum-Buchholz, A. (2018). A protocol for the intercomparison of marine fishery and  
1048 ecosystem models: Fish-MIP v1.0. *Geoscientific Model Development*, *11*, 1421–1442.  
1049 <https://doi.org/https://www.geosci-model-dev-discuss.net/gmd-2017-209/>

1050 Trebilco, R., Baum, J. K., Salomon, A. K., & Dulvy, N. K. (2013). Ecosystem ecology: Size-based  
1051 constraints on the pyramids of life. *Trends in Ecology and Evolution*, *28*(7), 423–431.  
1052 <https://doi.org/10.1016/j.tree.2013.03.008>

1053 van Denderen, D., Gislason, H., van den Heuvel, J., & Andersen, K. H. (2020). Global analysis  
1054 of fish growth rates shows weaker responses to temperature than metabolic predictions.  
1055 *Global Ecology and Biogeography*. <https://doi.org/10.1111/geb.13189>

1056 Veytia, D., Corney, S., Meiners, K. M., Kawaguchi, S., Murphy, E. J., & Bestley, S. (2020).  
1057 Circumpolar projections of Antarctic krill growth potential. *Nature Climate Change*, *10*(June),  
1058 568–575. <https://doi.org/10.1038/s41558-020-0758-4>

1059 Waldron, A., Adams, V. ., Allan, J. ., Arnell, A., Asner, G. ., Atkinson, S., & Baccini, A. (2020).  
1060 *Protecting 30 % of the planet for nature : costs , benefits and economic implications areal*  
1061 *protection in the draft post-2020 Global Biodiversity Framework*. Ottawa.

1062 Woodworth-Jefcoats, P. A., Polovina, J. J., Howell, E. A., & Blanchard, J. L. (2015). Two takes  
1063 on the ecosystem impacts of climate change and fishing: Comparing a size-based and a  
1064 species-based ecosystem model in the central North Pacific. *Progress in Oceanography*, *138*,  
1065 533–545. <https://doi.org/10.1016/j.pocean.2015.04.004>