

1 **Combining mesocosms with models to unravel the effects of global warming**
2 **and ocean acidification on temperate marine ecosystems**

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Running title: Mesocosm data improves biodiversity forecasts

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17 **Abstract**

- 18 1. Ocean warming and species exploitation have already caused large-scale
19 reorganization of biological communities across the world. Accurate projections of
20 future biodiversity change require a comprehensive understanding of how entire
21 communities respond to global change.
- 22 2. We combined a time-dynamic integrated food web modelling approach (Ecosim) with
23 a community-level mesocosm experiment to determine the independent and combined
24 effects of ocean warming and acidification, and fisheries exploitation, on a temperate
25 coastal ecosystem. The mesocosm enabled important physiological and behavioural
26 responses to climate stressors to be projected for trophic levels ranging from primary
27 producers to top predators, including sharks.
- 28 3. We show that under current-day rates of exploitation, warming and ocean acidification
29 will benefit most species in higher trophic levels (e.g. mammals, birds, demersal
30 finfish) in their current climate ranges, with the exception of small pelagic fish, but
31 these benefits will be reduced or lost when these physical stressors co-occur.
- 32 4. We show that increases in exploitation will, in most instances, suppress any positive
33 effects of human-driven climate change, causing individual species biomass to
34 decrease at high-trophic levels. Species diversity at the trailing edges of species
35 distributions is likely to decline in the face of ocean warming, acidification and
36 exploitation.
- 37 5. Synthesis and applications. We showcase how multi-level mesocosm food web
38 experiments can be used to directly inform dynamic food web models, enabling the
39 ecological processes that drive the responses of marine ecosystems to scenarios of
40 global change to be captured in model projections and their individual and combined
41 effects to be teased apart. Our approach for blending theoretical and empirical results

42 from mesocosm experiments with computational models will provide resource
43 managers and conservation biologists with improved tools for forecasting biodiversity
44 change and altered ecosystem processes due to climate change.

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46 Keywords: biodiversity change, fisheries exploitation, food web models, climate change,
47 multiple stressors, species interactions, trophic modelling

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49

50 **INTRODUCTION**

51

52 Marine ecosystems and resources are facing significant challenges due to the cumulative
53 effects of multiple global and local stressors, including overfishing, eutrophication, pollution,
54 habitat destruction, climate change, and ocean acidification (Cheung, 2018; Halpern et al.,
55 2015). Hence, significant effort is needed to generate reliable projections of future changes in
56 marine food webs and fisheries productivity.

57 Past attempts to forecast climate-driven changes in populations of fisheries species
58 have incorporated the direct impact of temperature on species physiology using deterministic
59 food web models (Blanchard et al., 2012; Brown et al., 2010), end-to-end climate models
60 (Olsen et al., 2018), and species distribution models (Cheung et al., 2011; Peterson et al.,
61 2002). Most of these projections, however, are based on species thermal niches or ecological
62 proxies that do not consider real time observations from the natural system or experimental
63 settings. Thus, they ignore the potentially large role of indirect (e.g. shifting predator-prey
64 relationships) and interactive drivers of change (e.g., with ocean acidification) on model
65 outcomes. Although thermal niches play an important role in governing species distributions
66 and their population sizes, the occurrence and abundance of species is also heavily regulated

67 by life-history traits, metapopulation processes and biotic interactions (Fordham et al., 2013;
68 Mellin et al., 2016). While modelling architectures have been developed to improve our
69 understanding of how multiple drivers of global change (including warming, acidification and
70 exploitation) interact and affect marine communities (Fulton and Gorton, 2014; Kaplan et al.,
71 2010; Koenigstein et al., 2018), accounting for complex biotic responses to multiple stressors
72 at the level of the food web has proved difficult.

73 The role of indirect effects of climate change (e.g. shifting predator-prey relationships)
74 on marine communities has received less attention than direct effects, even though they are
75 likely to strongly shape future marine communities (Lord et al., 2017; Nagelkerken et al.,
76 2017). Empirical data that enables biotic interactions to be quantified under near-future
77 climate change scenarios is urgently needed to better project and understand the role of direct
78 and indirect drivers of climate change on biological systems. A promising avenue is to use
79 large-scale mesocosm experiments to quantify the potential effect of global warming on the
80 strength of biotic interactions, rates of species turnover and composition, along with many
81 other key ecological processes that drive population- and community-level responses to
82 climate change (Fordham, 2015; Nagelkerken et al., 2020). Although scale, closed
83 boundaries, simplified ecological communities, and replication can impose challenges for
84 researchers using mesocosm experiments, they have the potential to quantify community-to-
85 ecosystem level responses to scenarios of global warming (Sagarin et al., 2016), particularly if
86 climate change mesocosm experiments align with regional climate projections for their study
87 system (Korell et al., 2020).

88 Dynamic food web simulation models have shown that scenarios of increased
89 temperature or acidification, modelled in isolation, could positively or negatively affect future
90 fisheries through increased primary productivity (Brown et al., 2010) or higher mortality of
91 invertebrates (Griffith et al., 2011; Marshall et al., 2017), respectively. However, the

92 cumulative effects of ocean warming and acidification on complex natural food webs remain
93 largely unknown, despite both stressors being a consequence of human-induced greenhouse
94 gas emissions, affecting marine systems in unison (Brierley and Kingsford, 2009).

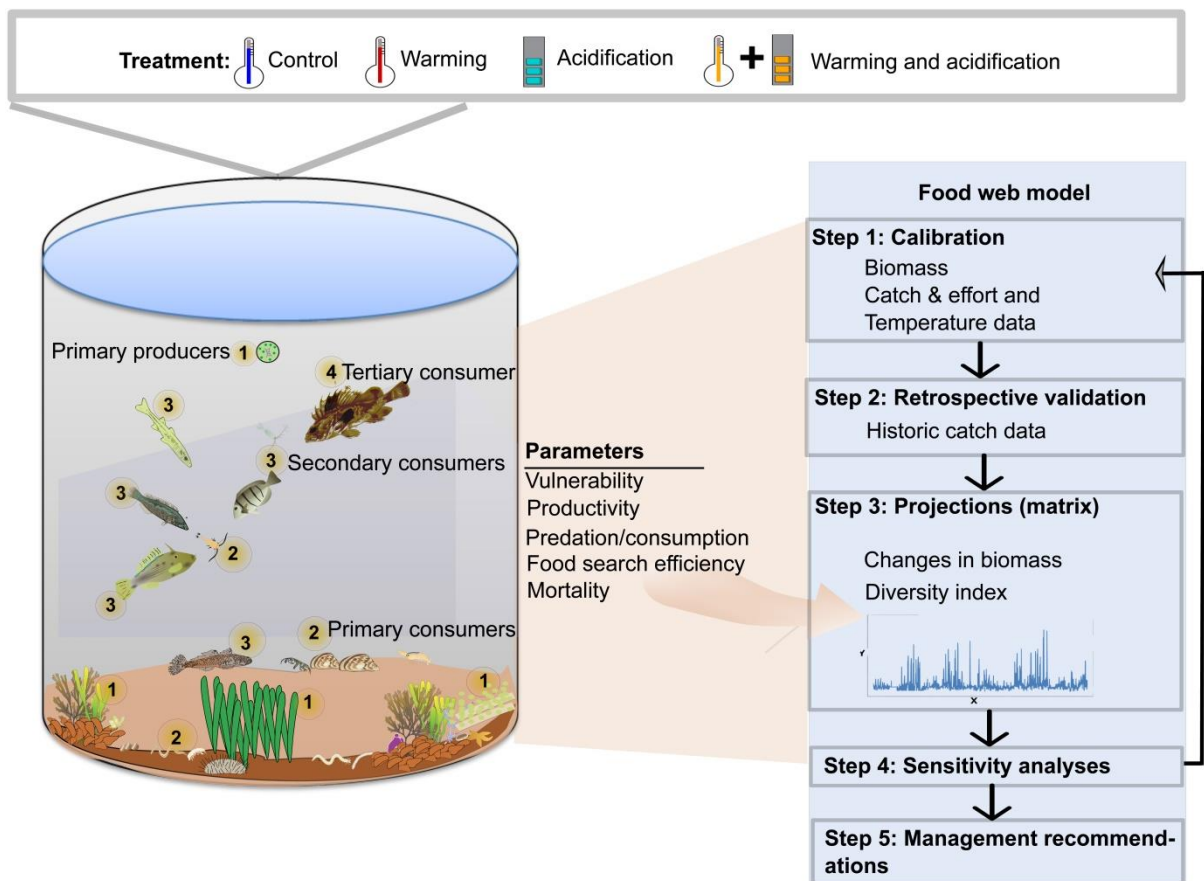
95 We combined empirical data from mesocosm experiments with dynamic food web
96 models to test whether: (1) the combination of ocean warming and acidification is likely to
97 exert synergistic, additive or antagonistic effects on food web structure and function for a
98 temperate coastal ecosystem, and (2) whether increased exploitation will amplify these
99 projected responses to increased greenhouse gas emissions. We use the mesocosm
100 experiments to integrate physiological and behavioral responses of organisms to different
101 scenarios of warming and/or acidification into the food web model, based on observations at
102 trophic levels ranging from primary producers to top predators (including sharks). We show
103 that integrating mesocosm experiments with dynamic food web models can provide
104 ecologically robust frameworks for exploring the consequences of climate change on the
105 structure and function of future food webs and their production capacity.

106

107 **MATERIALS AND METHODS**

108

109 We integrated empirical data from two food-web-level mesocosm studies (and other sources)
110 into an existing food web model for the Port Philip Bay (PPB) temperate coastal marine
111 ecosystem (Victoria, Australia) (Koopman, 2005) using Ecopath (Christensen et al., 2008).
112 We validated the food web model retrospectively, using hindcast validation and then
113 simulated likely future community-level changes for the PPB ecosystem (Fig 1).



114

115 Figure 1: Conceptual representation of how different food web parameters from mesocosm
 116 experiments can be integrated with dynamic modelling approaches to project the state of
 117 future ecosystems. Several trophic level groups are illustrated e.g.: 1) primary producers:
 118 phytoplankton, macroalgae, seagrass, algal turf, microphytobenthos; 2) primary consumers:
 119 gastropods, shrimps, copepods, bivalves, polychaetes, sea urchins, sea stars, sponges,
 120 ascidians, tanaids; 3) secondary consumers: carnivorous (pelagic) fish, omnivorous fish,
 121 herbivorous fish, carnivorous (benthic) fish; 4) tertiary consumer: scorpionfish (behavioural
 122 experiment). Organism symbols were drawn by the authors or were courtesy of the
 123 Integration and Application Network, University of Maryland Center for Environmental
 124 Science (ian.umces.edu/symbols/).

125

126 Food web model and scenarios

127 Ecopath is a mass-balance food-web modelling approach used to create a baseline snapshot of
 128 the ecosystem and quantify the flow of energy between food web functional groups
 129 (Christensen et al., 2008). The model requires four primary input variables: biomass (B),

130 production/biomass ratio (P/B), consumption/biomass ratio (Q/B), and diet composition.
131 Experimental data from two large-scale mesocosms (Pistevos et al., 2015; Ullah et al., 2018),
132 and field data published elsewhere, were used to calculate these input variables (see
133 Supporting Information).

134 Differential equations were used to estimate biomass fluxes for each species and/or
135 functional group within the food web using foraging arena theory (Ahrens et al., 2012).
136 Vulnerability parameters were used to define predator consumption rates (Q_{ij}) (Equation 1)
137 (see Supporting Information). For each predator-prey interaction, we calculated Q_{ij} at time t
138 as,

$$139 \quad Q_{ij}(t) = \frac{a_{ij} \times v_{ij} \times B_i(t) \times B_j(t) \times f(t)}{2 \times v_{ij} \times a_{ij} \times B_j(t)} \quad (\text{Eq. 1})$$

140 where a_{ij} is the effective search rate of predator j feeding on prey i , B_i is the biomass of the
141 prey, B_j is the predator biomass, and v_{ij} is the vulnerability of prey i to predator j (Christensen
142 et al., 2008). The forcing function $f(t)$ was used to account for external drivers changing
143 through time affecting Q_{ij} .

144 Climate change was incorporated into model projections using forcing functions that
145 temporally affect the consumption and production of functional groups (Ainsworth et al.,
146 2011; Cornwall and Eddy, 2015) based on observations from the mesocosm experiments (see
147 below). Specifically, we used the estimated effects of warming, acidification and their
148 combination on prey vulnerability, search activity (higher trophic levels), mortality and
149 productivity (primary producers) of trophic groups to alter modelled consumption (Q/B_i) and
150 production (P/ B_i) rate.

151 We developed four 85-year simulations (2015-2100): a no-climate-change scenario
152 (baseline), ocean warming (T), ocean acidification (OA) and their combination (OAT). The
153 climate change scenarios assumed a 2.8 °C increase in warming by 2100, representing a high
154 representative concentration pathway scenario (RCP 8.5) for the Port Phillip Bay region (1.9

155 to 3.8 °C increase from a 20-year baseline focused on 1995 (Clarke et al., 2011)). We
156 considered only RCP 8.5 because it was feasible to do the mesocosm experiment under only
157 one RCP scenario. Uncertainty in parameter estimates for biomass (B), production (P/B) and
158 consumption (Q/B) rates, and ecotrophic efficiency (EE) was simulated by varying these
159 parameters randomly within bounds of $\pm 20\%$ coefficient of variation.

160 The no-climate-change scenario (NC) assumes that model parameters do not change in
161 the future, with model drivers, including fishing effort, set to the last year of the historical
162 observation data (2015). For the three climate change scenarios (T, OA, and OAT), we
163 incorporated direct and indirect climate-driven changes in species interactions and mortality
164 of trophic functional groups in the food web. The effects of climate change were assessed by
165 comparing biomasses and ecological indicators observed under the NC scenario with that of
166 the climate change scenarios. Exploitation was initially held constant at 2015 levels for 21st
167 Century climate change scenarios because fisheries management is generally done at decadal
168 temporal resolutions, or finer (Fulton et al., 2018), meaning little is known about how
169 exploitation rates are likely to change by the end of the century. However, we did run further
170 scenarios to test the response of future food webs to increased exploitation. We did this by
171 increasing exploitation by 1.5, 2 and 5-fold compared to present-day fishing pressure.

172

173 **Mesocosm experiment**

174 Empirical data from the mesocosm experiments were used to quantify the effects of climate
175 change on food web structure and function, including trophic level biomass and diversity
176 (Fig. 1; Supporting Information). Three response variables were derived and combined to
177 estimate prey vulnerability to higher order trophic levels (trophic level ≥ 2) using behavioural
178 experiments under the different mesocosm treatments (NC, T, OA, OAT). I) “prey attraction”
179 was calculated as the percentage of time spent in the area close to a food cue relative to the

180 time spent in the entire field of view (Goldenberg et al., 2018). II) ‘food search activity’ was
181 given as the number of position changes in the area close to a food cue relative to the time
182 spent in this area (Goldenberg et al., 2017). III) ‘boldness’ was measured as the percentage of
183 time spent directly in front of a predator within the area close to a food cue relative to the time
184 spent in the entire area close to the food cue. We averaged across the three response variables,
185 weighting each variable equally, to obtain a composite vulnerability index of prey to its
186 predator. For chondrichthyans, we calculated effective search activity as the total time taken
187 by Port Jackson sharks (*Heterodontus portusjacksoni*) to successfully locate prey hidden in
188 the sand using olfactory cues (see methods in (Pistevos et al., 2015) for details). Mortality as a
189 direct function of biomass decline was quantified for functional groups not predated in the
190 system. Primary productivity was measured from community metabolism as gross oxygen
191 production ($\text{mg O}_2/\text{m}^3/\text{min}^1$) once per mesocosm at the end of the experiment. See Supporting
192 Information for more details.

193 We calculated relative effect sizes for prey vulnerability, search activity, mortality and
194 productivity by comparing the NC (control) scenarios with climate change treatments. These
195 effect sizes were used to derive the model forcing functions for different climate change
196 scenarios (OA, T, and OAT) (Table S1). The forcing function (input) and responses (biomass)
197 were standardized to the base scenario by dividing the response value by the base values
198 under a particular scenario. We used linear interpolation to construct a time series for all the
199 forcing function parameters between 2015 and 2100. While it is common practice in climate
200 change ecology to interpolate temporally between climate snapshots (Fordham et al., 2012),
201 doing so can potentially mask important decadal variation (Fordham et al., 2018). We were
202 limited to this approach because the mesocosm experiments were snapshots focussed on year
203 2100. The forcing functions were applied to appropriate functional groups in the model (Table

204 S1). We provide a more detailed explanation of the estimation of different forcing function
205 parameters in the Supporting Information.

206

207 **Analysis and model validation**

208 We pooled food web functional groups into 10 community levels, including pelagic groups
209 (mammals, birds, cephalopods, pelagic finfish), demersal groups (chondrichthians and
210 demersal finfish) and their prey (benthic crustaceans, invertebrates, small pelagic crustaceans,
211 primary producers) (Table S2). We calculated effect sizes for changes in biomass under
212 different model scenarios using Hedges' g (Lakens, 2013). We calculated and compared key
213 biodiversity indicators under different model scenarios, including the Shannon index
214 (Shannon and Weaver, 1963) and Kempton's Q index (Ainsworth and Pitcher, 2006). The
215 Shannon diversity index captures changes in evenness, whereas the Kempton's Q index
216 captures changes in both evenness and richness at the level of functional groups (see
217 Supporting Information for details).

218 We did an ecosystem model skill assessment (Olsen et al., 2016) and a global
219 sensitivity analysis (Fordham et al., 2016) to determine the influence of input parameters on
220 model results (see Supporting Information). To assess ecosystem model skill for our PBB
221 model — and verify that parameters from our mesocosm were transferrable to the PPB coastal
222 marine system — we validated hindcast simulations using independent catch-data (Table S3).
223 Historical abundances (1993 and 2011) were simulated using the full-PBB model and sub-
224 models with only functional groups in the mesocosm experiment. We assessed model-skill
225 using a wide range of metrics (Olsen et al., 2016; Stow et al., 2009): root mean squared error
226 (RMSE), average error (AE), average absolute error (AAE), modelling efficiency (MEF), and
227 Pearson (P) and Spearman (S) correlation.

228 We determined the sensitivity of Ecopath input parameters — biomass (B), production
229 (P/B) and consumption (Q/B) rates, and ecotrophic efficiency (EE) — on estimates of change
230 in biomass under a scenario of projected ocean warming and acidification (OAT) and a
231 scenario that included a moderate level of exploitation as well as OAT. To do this we used the
232 built-in Monte Carlo routine within Ecosim module, which allows model input parameters to
233 be varied (Coll and Steenbeek, 2017; Heymans et al., 2016). Specifically, we ran 100 Monte
234 Carlo simulations with B, P/B and Q/B and EE varying randomly within bounds of $\pm 20\%$
235 coefficient of variation. Initial and projected future biomass for 3 community groups
236 (cephalopods, pelagic finfish and invertebrates) were recorded for the year 2100. We used
237 generalized linear models (GLM) to explore the relative importance of different model input
238 parameters on projected changes in future biomass (Fordham et al., 2016). We did this by
239 calculating standardized regression coefficients (SRC) along with the coefficients and their
240 confidence intervals. Furthermore, we assessed the quality of input data for the PPB model
241 using food web diagnostics (Link, 2010) and explored the effects of parameter uncertainty on
242 model outputs using sensitivity analysis. See Supplementary Information for more details.

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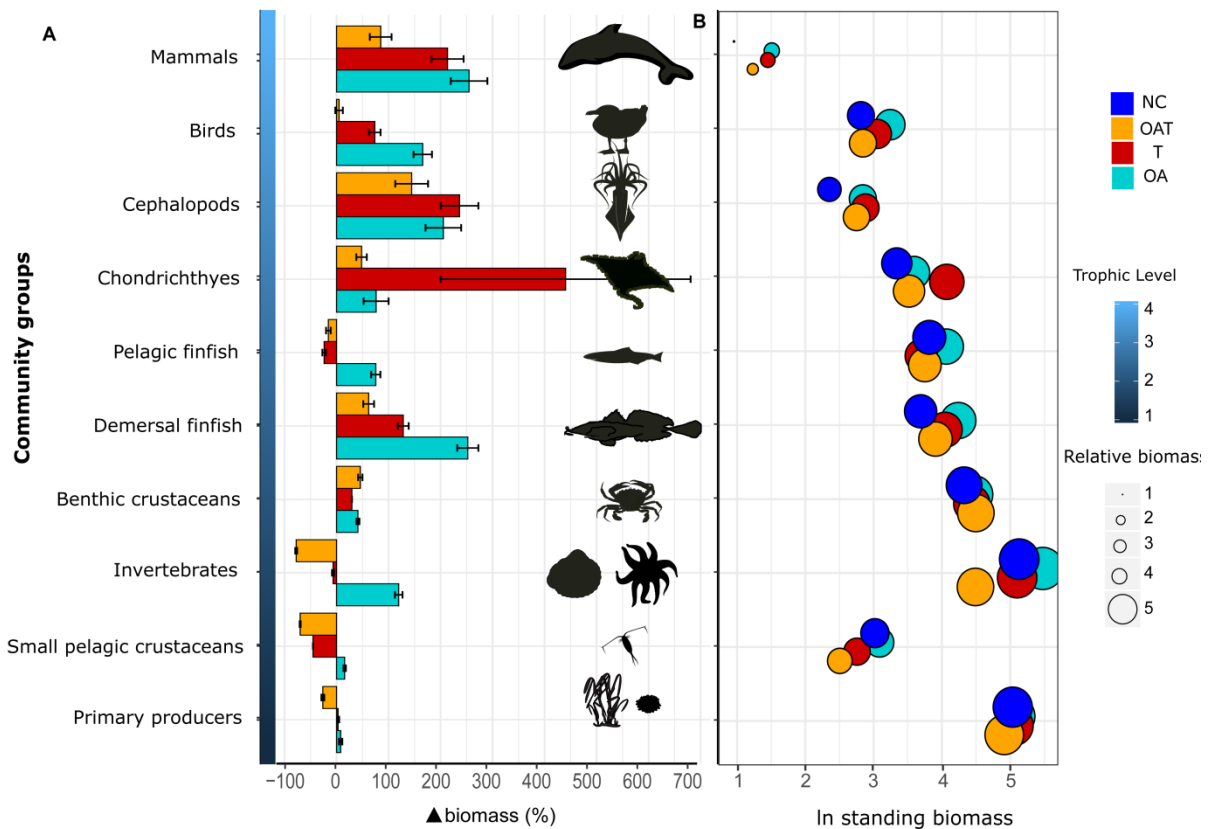
244 **RESULTS**

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246 **Biomass changes under future climate change**

247 Model simulations show that the total biomass of most higher-trophic-order community
248 groups (mammals, cephalopods, chondrichthians, and demersal finfish) is likely to benefit
249 from ocean warming (T) or acidification (OA), when modelled separately (Fig. 2, Fig S1).
250 However, the combination of the two stressors has an antagonistic effect on biomass increase.
251 At the level of individual species or functional group the positive effects on biomass are more
252 disparate (Figs. S2, S3).

253 Our models project an average increase in marine mammal biomass of 85% by the end
 254 of the 21st Century under the combined effect of acidification and warming (OAT) compared
 255 to no-climate-change and current levels of fish exploitation ('no change' scenario) (Fig. 2A).
 256 Modelling acidification (OA) and warming (T) separately resulted in even higher average
 257 increases in marine mammal biomass: 254% and 213%, respectively. Cephalopod biomass is
 258 projected to increase by 144% under OAT, while warming and acidification in isolation likely
 259 boost biomass by 237% and 205%, respectively. Although chondrichthyans showed the
 260 largest increase in their biomass under warming, this increase in biomass was affected by
 261 parameter uncertainty. Demersal finfish and seabirds are projected to increase their biomass
 262 the most in response to OA (252% and 165%, respectively), with a smaller increase under T.
 263 Pelagic finfish showed a negative response to warming, irrespective of acidification, with
 264 small pelagics (mostly planktivores) showing severe depletions (>70%) under both under T
 265 and OAT (Fig. S2).



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268 FIGURE 2:: A) Mean (\pm 95% confidence interval) relative change in biomass (Δ %) in year
269 2100 for different food web community groups under three climate change scenarios relative
270 to a no-climate-change (NC) scenario. OA = ocean acidification, T = ocean warming, and
271 OAT = combined ocean acidification and warming. Functional groups of food web models
272 are aggregated to community groups (CGs) for better representation and clarity. The order of
273 CGs is based on the mean trophic level (shown in blue). B) The future standing biomass
274 (kg/km^2 ; ln- transformed) estimates for each CG. The bubble size is proportional to its
275 biomass. Exploitation rates for all scenarios are modelled at present-day rates.

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278 Conversely, ocean warming – either alone or in combination with ocean acidification
279 – is projected to exert a negative effect on lower trophic-level faunal groups, with the
280 exception of benthic crustaceans (Fig. 2A). Invertebrates (predominantly molluscs and
281 invertebrates that do not possess a chitinous exoskeleton; Table S5), and small pelagic
282 crustaceans (zooplankton) are projected to experience biomass declines of 7-78% and 45-
283 70%, respectively, under T or OAT (Fig. 2).

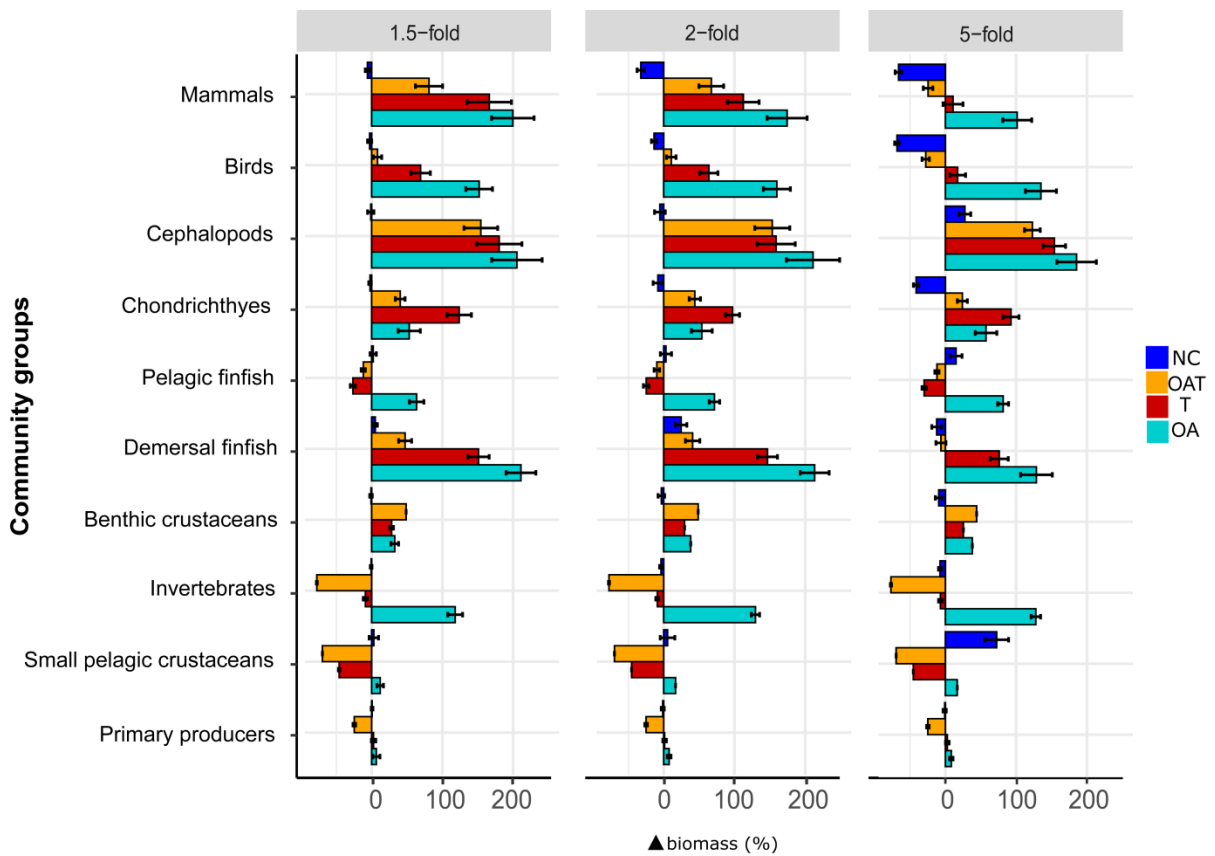
284 The standing biomass of primary producers increased under OA and T, but decreased
285 by \sim 26% under OAT (Fig. 1A), largely driven by a reduction of phytoplankton, micro-
286 phytobenthos and macro-algal biomass (Fig. S3). Turf algae, in contrast, experienced a large
287 increase in biomass (Fig. S3).

288

289 **The combined effect of warming, acidification and exploitation**

290 In the absence of ocean warming and acidification, exploitation reduced (by 1-32%) projected
291 biomass in the year 2100 for most higher-order community groups under a 1.5- to 2-fold
292 increase in exploitation rate (Fig. 3). Further increases in exploitation (up to 5-fold)
293 exacerbated this declining trend (by 41-66%) for mammals, birds (due to reduced prey) and
294 chondrichthians. Negative effects of up to a 2-fold increase in exploitation were suppressed at

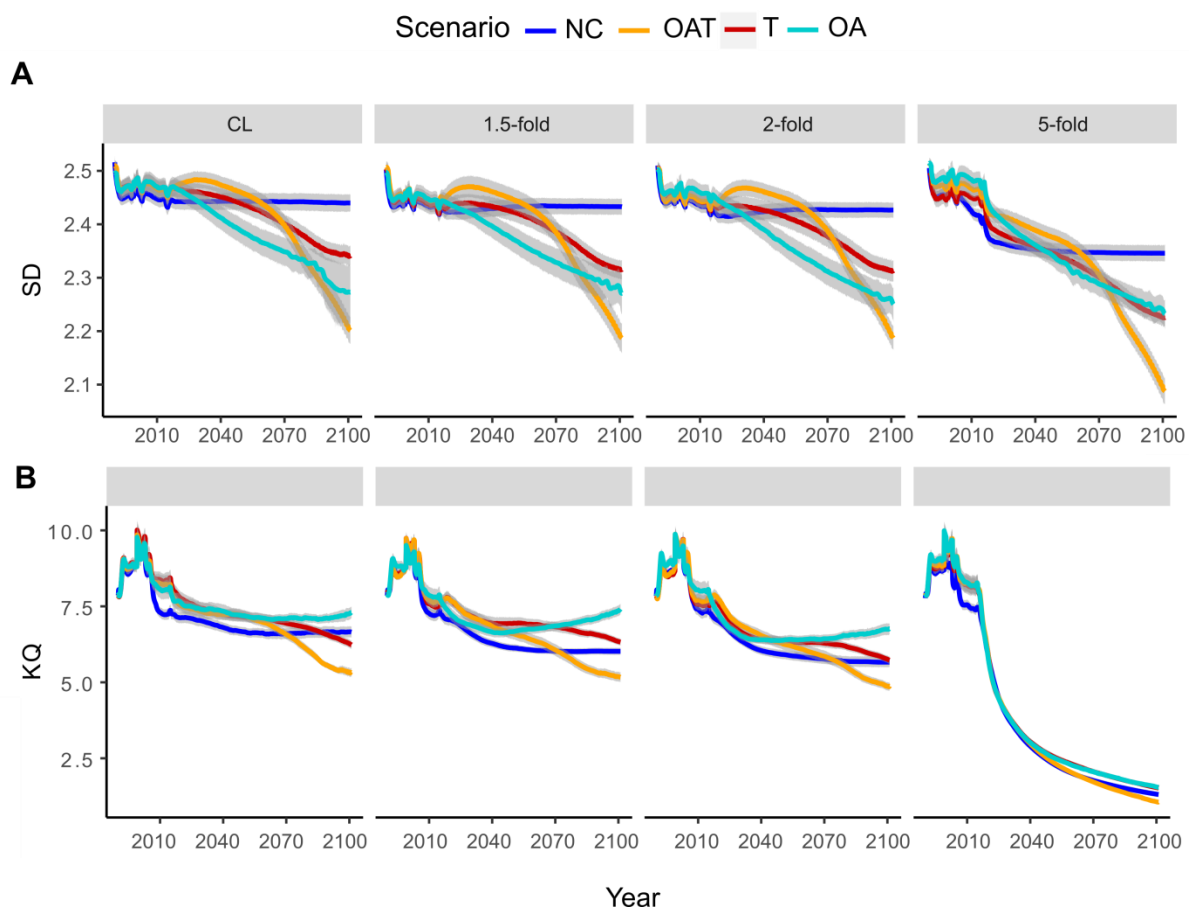
295 higher trophic levels (except for pelagic finfish) under modelled climate change (OA, T and
 296 OAT), due to greater top-down control of consumers on prey resources (Fig. 2). However, a
 297 5-fold increase in exploitation caused the biomass of mammals and birds to collapse under
 298 warming scenarios, causing some functional groups for example cephalopods to increase in
 299 biomass (T: 178%; OAT: 144%) (Fig. S4). Whilst both T and OA scenarios positively
 300 affected higher trophic levels in the face of medium-to-high increases in exploitation, their
 301 largely negative effects on lower trophic levels (primary producers, small pelagic crustaceans
 302 and invertebrates) were not decreased by increased exploitation (Fig. 3; Fig. S5).



303
 304 FIGURE 3: Mean (\pm 95% confidence interval) relative change in biomass (Δ %) in year 2100
 305 compared to no change in climate and fishing from present-day levels (NC). OA = ocean
 306 acidification, T= ocean warming, and OAT = combined ocean acidification and warming.
 307 Functional groups are aggregated to community groups (CGs) for better representation and
 308 clarity. Number of ‘folds’ equals the magnitude of increase in fishing pressure starting in
 309 2015.
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Under the NC scenario, the Shannon diversity index remained relatively stable in the future under 1.5- and 2- fold increases in exploitation, whilst it decreased by ~ 4% under a 5-fold increase in exploitation (Fig. 4A). In contrast, the Shannon diversity index declined under all global change scenarios with the largest declines projected for OAT, under a 5-fold increase in exploitation (Fig. 4A). The Kempton Q metric for higher trophic levels showed a stronger decline (after year 2070) under OAT compared to the other climate change scenarios (Fig. 4B). A 5-fold increase in exploitation resulted in a steep and immediate decline in the Kempton Q index regardless of the climate change scenario.



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FIGURE 4: Ecological indicators of change in community composition, showing A) Shannon diversity index and B) Kempton Q index. The grey shadows represent the 95% percentile and 5% percentile. NC = no change in climate from present-day levels, OA = ocean acidification,

325 T = ocean warming, and OAT = combined ocean acidification and warming. CL= current
326 level of fishing effort. Number of ‘folds’ equals the magnitude of increase in fishing pressure
327 starting in 2015.

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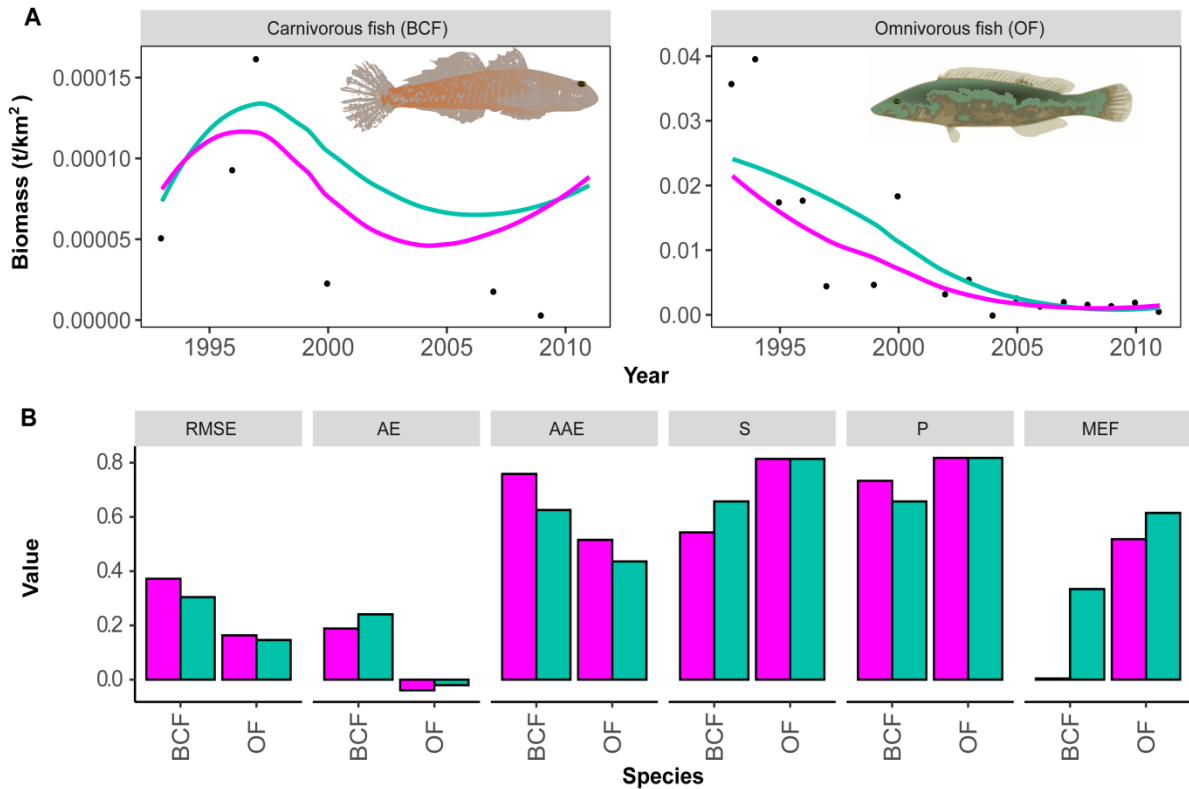
330 **Model validation and sensitivity**

331 Hindcasts of biomass from models parameterized using mesocosm data were correlated with
332 empirical field data for carnivorous fish and omnivorous fish (correlation coefficient [r] =
333 0.54-0.82). The food web model skill assessment showed that models parametrized with
334 mesocosm data are generally as skillful at projecting changes in biomass as models
335 parameterized with field data (Fig. 5). Model projections for carnivorous and omnivorous fish
336 biomass were relatively synchronous with independent biomass (survey) data, regardless of
337 whether the models were parameterized using empirical data from the field ($r = 0.73$, $RMSE$
338 ≤ 0.0001 ; $r = 0.82$, $RMSE = 0.007$, respectively) or mesocosm ($r = 0.69$, $RMSE \leq 0.0001$; $r =$
339 0.82 , $RMSE = 0.007$, respectively) data. Models parameterized with either field or mesocosm
340 data did worse at projecting observed temporal variability in biomass for Port Jackson shark (r
341 $= 0.12$, $RSME = 0.011$, $r = 0.29$, $RSME = 0.011$, respectively). Estimates of modelling
342 efficiency (MEF) suggest that models for omnivorous fish and carnivorous fish do better than
343 random (MEF > 0). This was not the case for Port Jackson sharks (Fig. S6). Importantly, bias
344 (average error) in model projections remained low for all functional groups for models
345 calibrated with field (carnivorous fish: + 0.24 g; omnivorous fish: - 0.02 g; Port Jackson
346 shark: -0.12 g) or mesocosm data (carnivorous fish: + 0.18 g; omnivorous fish: -0.03 g; Port
347 Jackson shark: -0.09 g).

348 The global sensitivity analysis (Table S6) showed that estimates of change in biomass
349 (years 2015 to 2100) under an OAT scenario for pelagic finfish and invertebrates are most
350 sensitive to changes in the Ecopath input parameter B followed by PB. For cephalopods,

351 estimates of change in biomass were most sensitive to changes in QB, followed by PB. The
 352 most important parameter for each community remained the same regardless of whether
 353 exploitation was modelled or not.

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 357 **FIGURE 5: A) Mesocosm transferability.** Comparison of the Port Phillip Bay (PPB) model
 358 built with the field (pink) and experimental data from the mesocosms (green) to standing
 359 catch biomass (tonnes per km²; solid black dots) for two major functional groups between
 360 years 1993 and 2011. BCF = benthic carnivorous fish and OF = omnivorous fish.

361 **B) Ecosystem model skill assessment** for models built using empirical field (pink) and
 362 experimental mesocosm data (green) for Port Phillip Bay (between 1993 and 2011): root
 363 mean squared error (RMSE), average error (AE), average absolute error (AAE), Spearman
 364 rank (S) and Pearson (P) correlation, and modelling efficiency (MEF) for 2 species. Y-axis
 365 limited to show values between -0.05 and 1.00.

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368 **DISCUSSION**

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370 By integrating empirical data on species physiological and behavioural performance from two
371 large-scale mesocosm experiments into dynamic food web models, accounting for historical
372 exploitation rates, we show that climate change is likely to benefit the biomass of animals at
373 higher trophic levels in some temperate marine ecosystems, albeit at a potential cost to
374 biodiversity. Increased biomass under warming results from strengthened top-down control of
375 consumers that occupy higher trophic levels, supported by a positive biomass response of
376 some of their prey groups. Accordingly, the structure of future temperate marine food webs
377 appears to be shaped by altered predator-prey dynamics, resulting from a reshuffling of
378 predatory and prey species abundances in response to warming, and not a continuous fuelling
379 of the food web from the bottom up as would be the case if ocean acidification was the
380 dominant climate stressor (Nagelkerken et al., 2020; Sswat et al., 2018).

381 Organisms at higher trophic levels are likely to increase their top-down control on
382 their prey, and therefore increase in biomass, in response to temperature-driven enhancements
383 in their metabolic rates (Brown et al., 2010). Although an increase in top-down control by
384 consumers has been previously suggested as a response to ocean warming for simplified
385 (three-trophic-level) food webs (Goldenberg et al., 2017; Marino et al., 2018), a robust
386 understanding of how higher-order consumers or apex predators will respond to global
387 warming, and the subsequent effects for lower-order trophic levels, has until now been
388 lacking. We show that under future scenarios of warming, the biomass of all higher-order
389 consumers and apex predators (mammals, birds, cephalopods, chondrichthians, and demersal
390 finfish) is likely to increase compared to a no-warming scenario due to amplified rates of prey
391 consumption (pelagic finfish, invertebrates and small pelagic crustaceans), driven, in part, by
392 increases in biomass of benthic crustaceans (major prey group in the system). Our new

393 results, for a temperate marine ecosystem, suggest that the benefit of warming for higher
394 trophic levels is likely to be universal, with associated negative effects for their prey at lower
395 trophic levels.

396 Acidification alone is not expected to enhance top-down control by consumers
397 because elevated CO₂ tends not to positively affect the metabolism of consumers (Carter et
398 al., 2013; Kroeker et al., 2013). Recent food web studies showed that enhanced primary
399 production can enlarge available prey resources, which can boost the growth of consumers
400 under acidification (Nagelkerken et al., 2017; Sswat et al., 2018). This was true for all higher-
401 order predators in our study, although for chondrichthians the biomass increase was weak.
402 Elevated CO₂ is known to affect the foraging behaviour (e.g. reduced prey search efficiency
403 and impaired odour tracking) of chondrichthians which might explain the reduced increase in
404 biomass for this group (Pistevos et al., 2015). Because of their different physiology, highly
405 active predators such as marine mammals, birds, and non-bony animals such as cephalopods
406 tend to be more tolerant to increasingly acidic environmental conditions (Melzner et al.,
407 2009). They benefit from amplified acidification only if increased resource availability at the
408 bottom of the food web is transferred up the food web.

409 Although warming and acidification in isolation showed striking positive effects on
410 the biomass of predators, their combined effect was antagonistic for many of the top
411 consumers in the food web and caused a decline in the biomass of many lower-order
412 consumers. Previous studies have shown that warming and acidification can antagonistically
413 affect the growth of carnivores such as sharks by affecting prey search time (Pistevos et al.,
414 2015), and of herbivores by increasing the degree of unpalatable or poor-quality food (Poore
415 et al., 2013). Two of the major prey groups in our model (small pelagic crustaceans and
416 invertebrates) experienced collapses in their biomass under the combined effect of warming

417 and acidification, reducing the availability of resources for higher level consumers, resulting
418 in reduced rates of change in consumer biomass under this scenario.

419 In contrast to other invertebrates, benthic crustaceans sustained a biomass increase
420 under all modelled climate scenarios, enabling an increase in the biomass of their consumers
421 (e.g. demersal fish, and consecutively some higher-order predators). Benthic crustaceans
422 (e.g. lobsters, crabs, and shrimp) are generally considered to have a higher tolerance to
423 acidification than other invertebrates (Kroeker et al., 2013) and show, in some cases, positive
424 responses to warming (Faulkner et al., 2014). These observations could explain their
425 successful propagation under scenarios of global warming.

426 Exploitation is a local stressor that negatively affected the biomass of all higher order
427 community groups, except pelagic finfish. However, warming and acidification negated these
428 negative effects, boosting the biomass of top predators at exploitation intensities equal to or
429 smaller than a two-fold increase. Global-scale models, with static fishing rates, suggest that
430 some commercial fisheries (ranging from crustaceans, small and large fish, to sharks) in high-
431 latitude regions could experience an increase in future catches, owing to temperature-driven
432 shifts in species distributional ranges (Cheung et al., 2010). However, we here limited our
433 findings to changes in food webs based on current species distributions (i.e. at their climate
434 trailing edges). Dynamic food web approaches also project a productivity increase in pelagic
435 fisheries in response to forecast warming of oceans (Blanchard et al., 2012), and increased
436 yields of commercially valuable fish stocks by 2050 under future warming (Merino et al.,
437 2012). While the latter studies modelled food web responses, they used a simplified approach,
438 with phytoplankton productivity as the only primary source of energy input, exploited species
439 as the primary elements of the food web, and ocean warming as a single stressor. Here, using
440 a more inclusive dynamic food web modelling approach, we show that opportunistic and less-
441 targeted groups such as cephalopods are likely to flourish in their biomass at higher fisheries

442 exploitation (\geq two-fold) rates due to a decrease in the biomass of major commercial species
443 such as demersal finfish irrespective of climate change. Overall, we show that the greatest
444 effects on future marine food webs are likely to arise at the top of the food web when
445 overexploitation coincides with the combined effect of warming and acidification.

446 Ocean warming and acidification have a much greater negative effect on functional
447 diversity in food webs than overexploitation. Future ocean warming and acidification can
448 significantly reduce diversity (i.e., Shannon diversity) within temperate coastal food webs
449 even under present-day exploitation levels, owing to declines in the biomass of primary
450 producers (i.e. non-weedy species such as macrophytes and certain species of phytoplankton),
451 small pelagic crustaceans, invertebrates, and pelagic fish species. Moreover, it can cause a
452 reduction in evenness (Kempton Q index) for higher-order groups in the food web. These
453 changes in diversity and evenness are likely to enable ecological opportunistic species to
454 flourish (Woodruff, 2001), such as high-order cephalopods and lower-order “weedy” turf
455 algae, leading to further simplification of community structure (Nagelkerken and Connell,
456 2015). Together, global warming and fishing will likely shift the distribution of biomass
457 within the community and reduced diversity of future food webs.

458 By combining empirical data on species response to climate change from large
459 mesocosms with historical population data (from scientific surveys and fisheries landings) in
460 a dynamic food web model, we moved from experimental ecology to making projections and
461 management recommendations aimed at safeguarding marine biodiversity under climate
462 change. Blending mesocosm experiments with “real world” ecological models has been
463 questioned on the grounds that they are unlikely to attain realistic projections (Carpenter,
464 1996). By independently validating our model projections against historical population data
465 (trawl surveys), we not only show that our dynamic food web model does a fair to good job at
466 reconstructing observed historical trends in biomass (particularly for selected functional

467 groups), but that models based on mesocosm experiments provide a relatively close
468 representation of ‘real world’ food webs. Therefore, mesocosms with realistic multifactorial
469 experiments that capture food web complexity can indeed be used with confidence to
470 parameterize ecosystem models and help to bridge the gap between simplified experimental
471 conditions and the real world.

472 Our modelling approach, like other modelling techniques, has its own caveats. El
473 Niño–Southern Oscillation (ENSO) is known to influence Australia’s marine ecosystem
474 through its year-to-year dynamics in climate variability (Lough and Hobday, 2011). These
475 fine temporal scale climate dynamics could not be captured in the mesocosm experiment and
476 therefore the food web model. This could, potentially, affect our modelled trajectories of
477 biomass and community composition. To calculate the vulnerability of fish to their
478 consumers, all fish species were considered into two major categories, namely carnivores and
479 omnivores (feeding guilds). The somewhat poor fit of modelled projections to observed data
480 for Port Jackson shark is likely to reflect an over-simplification of food web structure for the
481 validation exercise (see Supplementary Information). Likewise, important and unaccounted
482 uncertainties in the validation data (i.e., detection probability) could partly explain the
483 difference between predicted and observed patterns of temporal variability in biomass
484 (Guillera-Arroita, 2017). Despite these limitations, our study included the best available
485 historical data and the most robust estimates of physiology and behaviour responses to global
486 warming for a 4-trophic level temperate food web system.

487

488 **CONCLUSIONS**

489 Here we used a novel approach to simulate the effects of global warming, ocean acidification,
490 and fishing on the biomass and diversity of species in a temperate coastal ecosystem, using
491 experimental data on the effects of ocean warming and ocean acidification on species

492 interactions and physiology, and historical fisheries (survey and catch) data. By simulating the
493 potential magnitude and direction of biomass changes for different functional groups, we
494 show that the structure and function of future temperate marine food webs under ocean
495 warming is likely to be altered by predator-prey dynamics at the top of the food web rather
496 than changes from the bottom up. Consumers at higher trophic levels are likely to benefit
497 from ocean warming and acidification, but these benefits will be reduced or lost when these
498 stressors co-occur. More generally, we show that mesocosm experiments can be integrated
499 with food web models to better manage marine biodiversity in response to 21st century
500 climate change.

501

502 **DECLARATION OF INTEREST STATEMENT**

503 The authors have no conflicts of interest to declare.

504

505 **AUTHORS' CONTRIBUTIONS**

506 HU, IN and DF conceived the research; HU and SG collected the data; HU developed the
507 methods; HU analysed the data; HU, IN and DF wrote the manuscript; All authors contributed
508 to revisions and approved the final submission.

509

510 **DATA AVAILABILITY STATEMENT**

511 Data will be available via the Dryad Digital Repository upon the acceptance of the article.

512

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521

522 **Appendix A.** Supporting Information

523

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