

# 1           Drivers of plankton community structure in intermittent and 2           continuous coastal upwelling systems—from microscale in-situ imaging 3           to large scale patterns

4           **Moritz S Schmid<sup>1\*</sup>, Su Sponaugle<sup>1,2</sup>, Kelly R Sutherland<sup>3,4</sup>, Robert K Cowen<sup>1</sup>**

5           <sup>1</sup> Hatfield Marine Science Center, Oregon State University, Newport, Oregon, 97365, USA

6           <sup>2</sup> Department of Integrative Biology, Oregon State University, Corvallis, Oregon, 97331, USA

7           <sup>3</sup> Institute of Ecology and Evolution, University of Oregon, Eugene, Oregon, 97403, USA

8           <sup>4</sup> Oregon Institute of Marine Biology, University of Oregon, Charleston, Oregon, 97420, USA

9           **\* Correspondence:**

10           Corresponding Author

11           schmidm@oregonstate.edu

12           **Keywords: California Current, plankton community structure, microbial loop, upwelling,**  
13           **plankton imaging, climate change, machine learning, big data**

14

## 15           Abstract

16           Eastern Boundary Systems support major fisheries whose early life stages depend on upwelling  
17           production. Upwelling can be highly variable at the regional scale, with substantial repercussions for  
18           new productivity and microbial loop activity. A holistic assessment of plankton community structure  
19           is challenging due to the range in body forms and sizes of the taxa. Thus, studies that integrate the  
20           classic trophic web based on new production with the microbial loop are rare. Underwater imaging  
21           can overcome this limitation, and together with machine learning, enables fine resolution studies  
22           spanning large spatial scales. We used the In-situ Ichthyoplankton Imaging System (ISIIS) to  
23           investigate the drivers of plankton community structure in the northern California Current, sampled  
24           along the Newport Hydrographic (NH) and Trinidad Head (TR) lines, in OR and CA, respectively.  
25           The non-invasive imaging of particles and plankton (250µm –15cm) over 1644km (30 transects) in  
26           the winters and summers of 2018 and 2019 yielded 1.194 billion classified plankton images. The  
27           imaged plankton community ranged from protists, crustaceans, and gelatinous taxa to larval fishes.  
28           To assess community structure, >2000 single-taxon distribution profiles were analyzed using high  
29           resolution spatial correlations. Co-occurrences on the NH line were consistently significantly higher  
30           off-shelf while those at TR tended to be highest on-shelf. Taxa co-occurrences at TR increased  
31           significantly with upwelling strength and in 2019 TR summer co-occurrences were similar to those  
32           on the NH line. Random Forests models identified the concentrations of microbial loop taxa such as  
33           protists, *Oithona* copepods, and appendicularians as important drivers of co-occurrences at NH line,  
34           while at TR, cumulative upwelling and chlorophyll a were of the highest importance. Our results  
35           indicate that the microbial loop is actively driving plankton community structure in intermittent  
36           upwelling systems such as the NH line and may induce temporal stability. Where upwelling is more  
37           continuous such as at TR, primary production may dominate patterns of community structure,

38 obscuring the underlying role of the microbial loop. Future changes in upwelling strength are likely  
39 to disproportionately affect plankton community structure in continuous upwelling regions, while  
40 high microbial loop activity enhances community structure resilience.

41 **1 Introduction**

42 Community structure in an ecological system is defined as the interactions among organisms within  
43 the community (Verity and Smetacek, 1996; Smetacek, 2012; Lima-Mendez et al., 2015). Planktonic  
44 community structure in the ocean and the processes driving it determine energy transfer through the  
45 trophic web, setting up fisheries and top predators (Brown et al., 2004), as well as carbon sinks.  
46 Community structure can be assessed through the lens of taxa co-occurrence. As co-occurrence is  
47 driven by processes enabling coexistence within an ecosystem, such as niche separation (MacArthur,  
48 1958; Chesson et al., 2000; Lindegren et al., 2020), co-occurrences together with their biotic and  
49 abiotic environmental envelope describe ecologically important patterns that enable the investigation  
50 of community structure (HilleRisLambers et al., 2012; Williams et al., 2014; Ríos-Castro et al.,  
51 2022).

52

53 The oceanic environmental envelope is changing (Bakun et al., 1990; Doney et al., 2012; Bakun et  
54 al., 2015; Bograd et al., 2022). While climate change is a global phenomenon, key systems in which  
55 climate change has particularly strong effects are Eastern Boundary Upwelling Systems (EBUSs),  
56 due to the disproportional contribution of EBUSs to global ocean productivity and ecosystem  
57 services such as fisheries (Bograd et al., 2022). One such EBUS is the California Current Ecosystem  
58 which extends from British Columbia, Canada, to Baja California Sur in Mexico and exhibits strong  
59 physical and ecosystem variability on seasonal, interannual, and decadal time scales (Ware and  
60 Thomson, 2005; Barth et al., 2007; Checkley and Barth, 2009). The Northern California Current  
61 (NCC), extends from the northern border of the California Current Ecosystem southward to Cape  
62 Mendocino, CA, and encompasses variable oceanography.

63

64 Upwelling in the NCC varies with latitude and season, with distinct downwelling (winter) and  
65 upwelling (spring-summer) seasons off OR and WA contrasted with persistent, stronger upwelling  
66 off northern CA (Bograd et al., 2009; García-Reyes and Largier, 2012). During upwelling, cold,  
67 nutrient- and CO<sub>2</sub>-rich waters reach the euphotic zone (Barth et al., 2005; Kirincich et al., 2005;  
68 Hales et al., 2006), fueling high phytoplankton production (Dickson and Wheeler, 1995; Hales et al.,  
69 2006). Spring-summer upwelling typically occurs in intermittent events (3-10 d) and is demarcated  
70 by brief relaxation periods that cumulatively fuel strong primary and secondary production in the  
71 system (Hickey and Banas, 2003; Feinberg and Peterson, 2003; Shaw et al., 2010). The NCC shelf in  
72 mid and northern Oregon (e.g., Newport at 45°N) is relatively wide, allowing for higher retention of  
73 upwelled waters compared to southern OR and northern CA locations such as Cape Blanco (42.8°N)  
74 with a narrower shelf. Circulation tends to closely track bathymetry (Lentz and Chapman, 1989;  
75 Kirincich et al., 2005; Hickey and Banas, 2008), with the coastal upwelling jet meandering off the  
76 shelf south of Heceta Bank (Barth et al., 2000).

77

78 Tightly woven into the marine food web is the microbial loop, which enhances water column  
79 recycling of carbon and nutrients, making these available again to higher trophic levels (Turner et al.,

80 2015; Cavan et al., 2019). While the microbial loop is often associated with low-latitude marine  
81 ecosystems with low nutrient levels and more recycled production (Azam et al., 1983), the microbial  
82 loop is ever-present, even in temperate areas where upwelling is prevalent (Wilkerson et al., 1987;  
83 González et al., 2004). In intermittent upwelling regimes, smaller plankters associated with the  
84 microbial food web can become dominant (Mousseau et al., 1998). Though patterns and processes of  
85 microbial cycling have been extensively studied (Pomeroy, 1974; Azam et al., 1983; Kirchman,  
86 2010), its influence is rarely examined beyond lower trophic levels, and it is often ignored in  
87 upwelling systems where the primary focus has been on new production and classical food chains  
88 (but see Vargas et al., 2007).

89

90 The central importance of upwelling to the NCC comes with some negative consequences in the form  
91 of hypoxic and anoxic events. When low oxygen water is upwelled onto the shelf and phytoplankton  
92 blooms collapse, bottom water can quickly become depleted of oxygen (Chan et al., 2008; 2019).  
93 Increasingly frequent, such events are also associated with low pH (ocean acidification) conditions  
94 (Feely et al., 2008; Chan et al., 2019), both having significant negative effects on demersal habitats  
95 and organisms (Doney et al., 2020; Nagelkerken and Connell, 2022). Upwelling regimes are poised  
96 to shift as a result of changes in wind forcing due to global climate change (Bakun, 1990; Bakun et  
97 al., 2015; Buil et al., 2021). The resulting poleward intensification of upwelling and equatorward  
98 reduction in upwelling will most certainly affect new productivity and thus activity of the microbial  
99 loop. In particular, the northern NCC is predicted to experience more upwelling-favorable winds in  
100 the future (Buil et al., 2021).

101

102 Simultaneously, climate change has the potential to affect oceanographic processes at all spatial  
103 scales that comprise the environmental envelopes experienced by marine taxa. Effects are likely to be  
104 evident in taxa distributions, community composition, and community structure at scales ranging  
105 from microscale (e.g., predator-prey interactions, nutrient uptake in phytoplankton), fine scale (e.g.,  
106 plankton thin layers and internal waves), sub-mesoscale (e.g., coastal processes such as cross-shore  
107 transport and upwelling), mesoscale (e.g., eddies, wind stress curl), and large basin scale [e.g., marine  
108 heat waves, Pacific Decadal Oscillation (PDO); Bakun and Nelson, 1991; Denman and Gargett,  
109 1995; Mantua and Hare, 2002; Dickey and Bidigare, 2005; Prairie et al., 2012].

110

111 Historically, net-based plankton sampling has not adequately resolved planktonic communities at the  
112 micro-, and fine scales that are important for plankton dynamics (Haury et al., 1978; Yamazaki et al.,  
113 2002; Benoit-Bird et al., 2013; Schmid et al., 2019; Robinson et al., 2021). In response, in-situ  
114 imaging instruments have been developed over the past few decades (Ortner et al., 1979) that can  
115 overcome this limitation. Today a variety of systems exist that have been designed for specific tasks:  
116 for instance, UVP6 (Picheral et al., 2022), Zooglider (Ohman et al., 2019), PlanktonScope (Song et  
117 al., 2020), the Scripps Plankton Camera System (Orenstein et al., 2020), and the In-situ  
118 Ichthyoplankton Imaging System (ISIIS; Cowen and Guigand, 2008). Advantages of imaging  
119 systems include their non-destructive and high spatial resolution sampling capability (Lombard et al.,  
120 2019) as well as efficient imaging of plankton traits (Schmid et al., 2018; Vilgrain et al., 2021;  
121 Lertvilai and Jaffe, 2022). Data from imaging systems are often analyzed using machine learning due  
122 to the volume of data generated (Luo et al., 2018; Irisson et al., 2021). Together with additional

123 onboard sensors (e.g., fluorometers, oxygen probes, CTDs) these imaging systems can describe the  
124 plankton community and their environmental envelope with high spatial resolution, providing new  
125 insight into plankton community structure (Briseño-Avena et al., 2020; Robinson et al. 2021).

126

127 To investigate the drivers of planktonic community structure in the NCC ecosystem, we deployed the  
128 ISIIS along two cross-shelf transects that varied in their seasonal patterns of upwelling. Sampling  
129 across two seasons (winter and summer) for two years (2018, 2019), in conjunction with a deep  
130 learning data pipeline, yielded a very large dataset for examining plankton community structure. To  
131 obtain a holistic view of community structure we used a spatially explicit high-resolution correlation  
132 of taxa distributions. The co-occurrence of a wide range of organisms spanning from primary  
133 producers and protists, through gelatinous plankton and crustacean zooplankton, to larval fishes, in  
134 the context of their biotic and abiotic environment was used to disentangle the degree to which  
135 community structure is driven by upwelling strength and new productivity versus the potential  
136 impact of the microbial loop. With climate change beginning to affect the California Current  
137 Ecosystem, it is important to identify current drivers of plankton community structure such that we  
138 can better anticipate future changes to the structure of the water column that may disrupt the costal  
139 marine food web including valuable fisheries.

140 **2 Materials and Methods**

141 **2.1 Study area**

142 Thirty transects ranging between 24 and 86 km in length were sampled along the Newport  
143 Hydrographic (NH) line as well as the Trinidad Head (TR) line during the winters (February-March)  
144 and summers (July-August) of 2018 and 2019. Located off Newport, Oregon (Fig. 1), the NH Line  
145 has been sampled since 1961 (Peterson and Miller, 1975), while the TR line off northern California  
146 has been sampled since 2007 (Robertson and Bjorkstedt, 2020). Both transects are part of regular net-  
147 based sampling efforts by the National Oceanic and Atmospheric Administration (NOAA) with a  
148 focus on determining the plankton community structure and the biophysical drivers of the  
149 recruitment of commercially important fishes. Imagery data were collected during both day and night  
150 hours, with daytime transects commencing at least 1h after sunrise and ending at least 1h before  
151 sunset, and nighttime transects commencing at least 1h after sunset and ending at least 1h before  
152 sunrise.

153 **2.2 In-situ Ichthyoplankton Imaging System (ISIIS)**

154 ISIIS (Cowen and Guigand, 2008) is a towed shadowgraph and line-scan imaging system, that scans  
155 a large volume of water ( $150 - 185 \text{ L}^{-1}$ ) to quantitatively sample abundant meso-zooplankton as well  
156 as rarer ichthyoplankton (Cowen et al., 2013). ISIIS's large imaging frame, with a  $13 \times 13\text{-cm}$  field of  
157 view and 50 cm depth of field allows for the undisturbed imaging of a variety of plankton taxa  
158 including fragile gelatinous zooplankton (McClatchie et al., 2012; Luo et al., 2014). The resulting  
159 images have a pixel resolution of 66  $\mu\text{m}$  and are recorded as continuous videography. Data are sent to  
160 a top-side computer using a fiber optic cable where ISIIS data are time-stamped. ISIIS is equipped  
161 with a CTD (Sea-Bird SBE 49 FastCAT), as well as a dissolved oxygen probe (Sea-Bird 43),  
162 fluorescence sensor (Wet Labs FLRT), and photosynthetically active radiation sensor (PAR;  
163 Biospherical QCP-2300). ISIIS is towed behind the ship at  $2.5 \text{ m s}^{-1}$  where it undulates on each  
164 cross-shelf transect between 1 m and 100 m depth or as close as 2 m above the seafloor in shallower  
165 water. ISIIS has been used in various ecosystems with differing scientific objectives, such as the

166 investigation of larval fish distributions at eddy fronts (Schmid et al., 2020) and fine-scale plankton  
167 patchiness in the Straits of Florida (Robinson et al., 2021), larval fish distributions in the context  
168 environmental gradients in the NCC (Swieca et al., 2020; Briseño-Avena et al., 2020), the  
169 investigation of zooplankton individual-level interactions and parasitism in the Gulf of Mexico  
170 (Greer et al., 2021), and cross-ecosystem comparisons of a gelatinous grazer (Greer et al., 2023).

171 **2.3 Sparse convolutional neural net**

172 ISIIS imagery data were processed following Luo et al. (2018) and Schmid et al. (2020), with a full  
173 open-sourced, pipeline code (Schmid et al., 2021). After the collected video data were flat-fielded  
174 and segmented into single regions of interest (ROIs; i.e., a single plankton specimen) using a k-  
175 harmonic means clustering algorithm, a training library of images was created by choosing  
176 representative images from all 2018 and 2019 transects. The training library contained 82,909 images  
177 spanning 170 different classes, ranging from protists and phytoplankton to larval fishes. The sCNN  
178 (SparseConvNets with Fractional Max□Pooling; Graham et al., 2015; Luo et al. 2018) was trained  
179 until the error rate plateaued at ~ 5% after 399 epochs.

180

181 The 170 original classes in the training library were mapped onto 67 broader groups (e.g.,  
182 chaetognaths of different shapes merged into one group). After removing five different unknown  
183 groups, 62 taxonomic groups remained for ecological analyses. A random subset of images was  
184 classified by two human annotators and used for probability filtering following Faillettaz et al.  
185 (2016), an approach that removes very low probability images from the dataset, achieving 90%  
186 predictive accuracy per taxon. Removal of these “low□confidence images” still allows for the  
187 prediction of true spatial distributions (Faillettaz et al., 2016). An independent subsample of the  
188 remaining images was again classified by the same two human annotators and the results compared  
189 with the automated classification. The resulting confusion matrix was used to calculate taxon-specific  
190 correction factors:

191

192 
$$(\text{Correction factor}(\text{taxon}) = \text{Precision}(\text{taxon})/\text{Recall}(\text{taxon})).$$

193

194 Individuals and environmental data were binned into 1 m vertical strata and plankton concentrations  
195 (ind.  $\text{m}^{-3}$ ) estimated based on the volume of imaged seawater. Plankton concentrations were then  
196 adjusted by applying the taxon-specific correction factors.

197 **2.4 Environmental and ecological data analyses**

198 To estimate the upwelling strength on each transect, we calculated the cumulative daily Coastal  
199 Upwelling Transport Index (CUTI<sup>1</sup>; Jacox et al., 2018) for the 10 d prior to sampling of a transect.  
200 This period was selected to account for the lag between physical forcing (i.e., nutrient upwelling) and  
201 phyto- (~7 d) and zooplankton (~13-16 d) abundances (Spitz et al., 2005). To encompass plankton  
202 ranging from phyto- to zooplankton, we selected an intermediate lag of 10 d (Swieca et al., *in*

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<sup>1</sup> ; <https://mjacox.com/upwelling-indices/>

203 *review*). Plankton community structure was assessed in two approaches using spatially explicit  
204 Spearman rank correlations as measure of the co-occurrence of taxa.

205 **2.4.1 Low spatial resolution taxa co-occurrence**

206 To better describe the environmental drivers of species distributions, transects were divided into an  
207 on-shelf portion and off-shelf portion based on the longitude of the 200 m isobath. Spearman rank  
208 correlations between the concentrations of each taxon and the remainder of the plankton community  
209 were calculated for both portions of a transect, with the underlying data binned vertically in 1-m  
210 strata (Fig. 2). Thus, each taxon was correlated 122 times per transect: 61 correlations with the other  
211 taxa on the shelf, and 61 correlations with other taxa off the shelf. Correlations were computed for all  
212 possible combinations of the 62 taxa along the 30 transects and only correlations that were significant  
213 at  $p < 0.01$  were used for further analyses.

214

215 Co-occurrences were compared between the two years, seasons, study sites, and shelf condition (on-  
216 and off-shelf). To determine whether on-shelf and off-shelf co-occurrences differed among the  
217 different years, seasons, sites, and shelf conditions, we used Wilcoxon Rank Sum tests with a  
218 confidence level of 0.999. To delineate patterns of taxa co-occurrences, coefficients of variation of  
219 the co-occurrences were calculated for each possible year, season, site, and shelf condition  
220 combination. Finally, to test for differences between NH and TR, the co-occurrences were regressed  
221 against CUTI at the two different study sites using a Wilcoxon Rank Sum test.

222 **2.4.2 High spatial resolution taxa co-occurrence and their environmental drivers**

223 Based on the original 1-m vertically stratified data, mixed layer depth (Kara et al., 2000), Brunt  
224 Vaisala Frequency, and geostrophic dynamic height anomalies (both using ‘gsw’ R package which  
225 follows TEOS-10 definitions) were calculated along each transect to account for mixing depth,  
226 stratification strength, and influence of the upwelling front, respectively. The data were then  
227 projected onto a 10-m vertically stratified grid while keeping the underlying 1 m vertical data  
228 structure intact. Spearman rank correlations were calculated similarly to 2.4.1, but instead of  
229 calculating one correlation for a taxon per on- or off-shelf, the 10 m grid was used to calculate a  
230 correlation for each 10 m interval of the water column. This enabled the retention of both vertically  
231 stratified environmental and co-occurrence data. Only Spearman rank correlations that were  
232 significant at  $p < 0.01$  were used in further analyses.

233

234 Resulting environmental and taxon-specific data (Table 1) were used in two Random Forests models,  
235 one for each of the two transect lines. In each case the modeled response variable was the correlation  
236 coefficient for a specific 10-m vertical section of the grid; however, all data collected on NH or TR  
237 were combined for the most generalist model. Random Forest analysis (Breiman et al., 2001) was  
238 carried out using the ‘caret’ package in R (Kuhn et al., 2008), in the ‘ranger’ RF implementation, and  
239 variable importance was assessed based on permutation importance. Partial dependence plots were  
240 used to investigate the specific non-linear effects of the 10 most important explanatory variables per  
241 model.

242

243 **3 Results**

244  
245 1.194 billion plankton images were classified based on 195 h of underwater imagery, traversing a  
246 total of 1644 km along 30 transects ranging from 24-86 km (Supplementary Material Table S1). The  
247 vast diversity of NCC plankton imaged included taxa such as appendicularians, crab zoea and  
248 megalopa, different types of copepods as well as hydromedusae, pteropods, chaetognaths,  
249 ctenophores, salps, several groups of larval fish (Fig. 3, Supplementary Material Table S1), among  
250 others. Dense thin layers of different plankton taxa were observed frequently during deployments and  
251 analysis of the imagery showed these dense layers consisted of  $> 25,000$  calanoid copepods per  $\text{m}^{-3}$   
252 (Feb 2018 on the TR line, Supplementary Material Table S1), or of  $> 1,300$  crab zoea per  $\text{m}^{-3}$  (Feb  
253 2018 on the NH line). Thin dense layers of doliolids reached densities of  $> 11,000$  individuals per  $\text{m}^{-3}$   
254 (e.g., NH line in July 2018), while lobate ctenophores accumulated to  $> 800$  individuals per  $\text{m}^{-3}$   
255 (March 2019 on the NH line). Appendicularian accumulations of  $> 10,000$  individuals per  $\text{m}^{-3}$  were  
256 found on the TR line in July 2019.

257  
258 Comparison of the environmental conditions at the NH and TR lines revealed distinct upwelling  
259 signatures in seawater densities along both sampling lines in the summers of 2018 and 2019 (see  
260 representative transects in Figs. 4, 5). Winter upwelling was less evident in TR line pycnoclines, but  
261 more so in cumulative CUTI upwelling 10 d prior to sampling (Fig. 6). Sea surface temperatures on  
262 the NH line peaked at  $17.5^\circ\text{C}$  in 2018, while water on the TR line remained substantially cooler.  
263 Surface salinities at the NH line were relatively fresh at 30, while most of the water column on the  
264 TR line was  $> 32.5$ . Oxygen levels fell to  $< 2 \text{ ml l}^{-1}$  levels on the NH line in summer 2018, coinciding  
265 with substantial upwelling. Chlorophyll *a* was highest on the TR line in summer 2018 with levels  
266 reaching up to  $45 \mu\text{g l}^{-1}$ . The temperature profile along the NH line in summer 2019 closely  
267 mimicked that of 2018, with surface temperatures  $> 17.5^\circ\text{C}$  (Fig. 5). In 2019, oxygen levels fell to  $<$   
268  $3 \text{ ml l}^{-1}$  in summer in near-bottom areas on the shelf, while sub-surface chlorophyll maxima reached  
269  $7.5 \mu\text{g l}^{-1}$  at both sampling sites in summer.

270  
271 Cumulative CUTI upwelling 10 d prior to sampling each transect was always higher on the TR line  
272 relative to the NH line (Fig. 6). The mean 10-day CUTI for the NH line during winter 2018 was  $3.8 \text{ m}^{-3} \text{ s}^{-1}$ , while it was  $4.8 \text{ m}^{-3} \text{ s}^{-1}$  during summer (Fig. 6). Upwelling in 2019 was markedly lower, with  
273 a mean of  $0.4 \text{ m}^{-3} \text{ s}^{-1}$  during winter and  $3.6 \text{ m}^{-3} \text{ s}^{-1}$  during summer. On the TR line, 2018 10-d CUTI  
274 upwelling reached  $13.8 \text{ m}^{-3} \text{ s}^{-1}$  and  $22.3 \text{ m}^{-3} \text{ s}^{-1}$  during winter and summer, respectively, while  
275 upwelling in 2019 followed the NH trend and was reduced to  $3.3 \text{ m}^{-3} \text{ s}^{-1}$  and  $6.2 \text{ m}^{-3} \text{ s}^{-1}$  during winter  
276 and summer, respectively.

277  
278 TS-diagrams demonstrate that temperatures on the NH line in summer were consistently the highest  
279 ones measured during the study (Fig. 7). Winter profiles were characterized by a substantially smaller  
280 water temperature range on both transects. While warm summer surface waters on the NH line were  
281 also the freshest found at either site, winter water was fresher on the TR line than on the NH line.  
282 Winter and summer water at both sampling sites showed a distinct seasonal signal (Fig. 7).

283 **3.1 Low spatial resolution taxa co-occurrences**

284 Co-occurrences among taxa ranged from strongly negatively correlated at -1 to strongly positively  
285 correlated at +1, with substantial intra-, and inter- taxon variation (Figs. 8, 9; not all extreme values  
286 are visible in the boxplots). Mean co-occurrences of all taxa differed significantly between on-shelf  
287 and off-shelf (Wilcoxon Rank Sum test, all combinations  $p < 0.0001$ , except winter of 2019 at TR)  
288 and these on-shelf/off-shelf patterns differed between the NH and TR lines (Figs. 8, 9). On the NH  
289

291 line, across both seasons and years, correlation coefficients were more positive off-shelf compared to  
292 on-shelf, while on the TR line the pattern was more complex. Winter and summer 2018 correlations  
293 on the TR line were the opposite of the NH line, with more positive correlations on-shelf relative to  
294 off-shelf. In contrast, average TR on- and off-shelf correlations in winter 2019 were virtually  
295 indistinguishable, before transitioning in summer 2019 to a pattern similar to the NH line where off-  
296 shelf correlations were significantly higher than those on-shelf.  
297

298 Similarly, the coefficients of variation (CVs) around these mean co-occurrences on the NH line were  
299 consistently higher on-shelf ( $> 2$ ) compared to off-shelf (1.5), while on the TR line, the pattern was  
300 more complex (Fig. 10). In winter 2018, CVs for both on-shelf and off-shelf correlations on TR were  
301 virtually identical, while in summer 2018, the on-shelf CV was lower than off-shelf, before switching  
302 to a pattern similar to the NH line in 2019, with higher CVs on-shelf relative to off-shelf (Fig. 10).  
303 Mean co-occurrence of all taxa as a function of the preceding 10-d cumulative CUTI was significant  
304 on the TR Line (Fig. 11; Wilcoxon rank sum test  $p < 0.001$ ), while on the NH line no such  
305 relationship was detected.  
306

### 307 **3.2 High spatial resolution taxa co-occurrence and their environmental drivers**

308 The two Random Forests (RF) models designed to predict vertically and horizontally stratified taxa  
309 co-occurrences based on 83 biotic and abiotic variables (Table 1) explained 42% (NH) and 43% (TR)  
310 of the variance. The variables explaining most of the variance per model differed substantially  
311 between the two transect locations (Fig. 12). On the NH line, sampling depth was the most important  
312 predictor, followed by the binary on-shelf/off-shelf variable, temperature, density, the distance along  
313 the transect (i.e., how far offshore sampling occurred), and salinity (Fig. 12). These abiotic variables  
314 were followed by taxa concentrations of *Oithona* sp. copepods, appendicularians, other small  
315 copepods, and protists. On the TR line, the binary year variable (2018/2019) was the most important  
316 predictor, followed by the 10-d cumulative CUTI, the binary shelf indicator, sampling depth, the  
317 distance along the transect, oxygen, density, temperature, chl *a*, and salinity (Fig. 12).  
318

319 On the NH line, a deeper sampling depth ( $> 85$  m) led to a substantially higher chance of co-  
320 occurrence than in shallower water, while on-shelf in general predicted lower co-occurrences (Fig.  
321 13). Temperature followed a gradual pattern where warmer temperatures predicted higher co-  
322 occurrence values. Density and salinity effects were similar in that the lowest densities and salinities  
323 led to the lowest co-occurrence and vice versa. Distance along the transect indicated that locations  
324 farther offshore predicted higher co-occurrences compared to inshore locations. Concentrations of  
325 *Oithona* copepods, appendicularians, other small copepods, and protists had similar effects in that  
326 their lowest concentrations predicted the least likely co-occurrence, followed by a rise in predicted  
327 co-occurrence as taxa concentrations increased. Protists showed the strongest such effect whereby a  
328 steady increase in protist concentrations led to the fastest increase in predicted co-occurrence,  
329 matched only by sampling depth.  
330

331 On the TR line, 2018 data were a good predictor of higher co-occurrence, while 2019 data led to  
332 lower values (Fig. 13). The 10-d cumulative CUTI was an important predictor and increasing CUTI  
333 values led to higher predicted co-occurrence until a CUTI of  $\sim 20 \text{ m}^{-3} \text{ s}^{-1}$ , after which the predicted  
334 co-occurrence dropped (Fig. 13). Notable differences between the TR and NH lines were that the  
335 shelf variable in the TR model showed that higher co-occurrence was predicted at on-shelf locations,  
336 which was followed by the distance variable that showed a decline in the predicted co-occurrence  
337 going from on-shore to off-shore. While the depth variable on the TR line also showed the highest  
338 predicted co-occurrence at 100m depth, the range of the predicted co-occurrences was substantially  
339 narrower than that on the NH line. Oxygen, density, and temperature partial effects plots had a very

340 similar pattern between locations: the lowest and highest values generally led to the highest predicted  
341 co-occurrence. The positive effect of Chl *a* on the co-occurrence of taxa increased steadily across the  
342 spectrum of chl *a* values ( $>20 \mu\text{g l}^{-1}$ ). The salinity partial effects profile differed substantially  
343 between locations: in contrast to the NH line, the highest salinities on the TR line were good  
344 predictors of higher taxa co-occurrence.

345

## 346 4 Discussion

### 347 4.1 Plankton community structure in the Northern California Current

348

349 As the northern portion of the prototypical Eastern Boundary Upwelling System, the northern  
350 California Current (NCC) is characterized by strong, but intermittent upwelling, a typically short  
351 food web, and subsequently high fisheries biomass (Ryther, 1969; Pauly and Christensen, 1995;  
352 Rykaczewski and Checkley, 2008). While plankton community structure in the NCC has received  
353 much attention over the last decades (Peterson and Keister, 2003; Peterson et al., 2014, 2017;  
354 Brodeur et al., 2019; Weber et al., 2021; Thompson et al., 2022), we still lack a comprehensive  
355 understanding of how plankton community structure responds to changing environmental conditions.  
356 Our high-resolution imaging of the water column at two locations in the NCC that differ in their scale  
357 and continuity of upwelling enabled us to tease apart the relationships of new and recycled  
358 production (i.e., microbial loop) and plankton community structure. By simultaneously sampling a  
359 wide range of organisms including protists, phytoplankton, zooplankton, and fragile gelatinous  
360 plankton, in situ plankton imaging can bridge the sampling gap in studying the microbial and new  
361 production driven components of the plankton (Biard et al., 2016; Briseño-Avena et al., 2020;  
362 Schmid et al., 2020).

363

364 Using plankton co-occurrence as a proxy for community structure (Reese and Brodeur, 2006;  
365 Brodeur et al., 2008; Sildever et al., 2021; Costas-Selas et al., 2022), we condensed  $>2000$  high  
366 resolution taxa distribution profiles into a unified community approach. Plankton co-occurrence  
367 patterns differed substantially between the two sampled locations, NH with intermittent upwelling  
368 and TR with more continuous upwelling. TR plankton co-occurrences in 2018 were higher on-shore  
369 relative to off-shore, consistent with the expectations for a nearshore upwelling system where new  
370 productivity is fueled by nutrients brought to the euphotic zone (Barth et al., 2007; Bograd et al.,  
371 2009; Jacox et al., 2018). However, TR plankton co-occurrences in 2019 differed from this pattern,  
372 likely induced by much lower upwelling and hence chl *a* in 2019. In sharp contrast to TR, plankton  
373 co-occurrence at NH was consistently higher in the more oligotrophic off-shelf waters (Peterson et  
374 al., 2017) relative to on-shelf waters. This pattern at NH remained consistent across all years and  
375 seasons, despite the lower upwelling in 2019 and suggests that in intermittent upwelling, nearshore  
376 conditions are generally less conducive to setting up a stable plankton community structure.

377

378 The relative importance of the microbial loop was highlighted by the high spatial resolution modeling  
379 of plankton co-occurrences. Among the variables explaining the most variance in taxa co-occurrence  
380 on the NH line over time were concentrations of several taxa associated with the microbial loop.  
381 *Oithona* sp copepods are small, ubiquitous cyclopoid copepods that are closely linked to the  
382 microbial loop through feeding on protozooplankton such as ciliates and dinoflagellates (Atienza et  
383 al, 2006; Zamora-Terol et al., 2014). Appendicularians similarly feed on the very small constituents  
384 of the microbial loop - down to picoplankton sizes - (Gorsky and Fenaux, 1998; Sutherland et al.,  
385 2010; Sutherland and Thompson, 2022) by using specialized feeding-filters (Conley and Sutherland,  
386 2017). Appendicularians can be extremely abundant – we measured dense patches of  $>10,000 \text{ ind. m}^{-3}$   
387 on the TR line – and are important prey for numerous taxa, including copepods, chaetognaths,  
388 ctenophores, and larval to small adult fishes (Gorsky and Fenaux, 1998; Purcell et al., 2005). Being a

389 key driver of plankton community structure on the NH line, while also accumulating in dense patches  
390 on the TR line, the presence of appendicularians indicates the constant underlying activity of the  
391 microbial loop. A key feature of appendicularians are their mucous houses that are discarded  
392 regularly and contribute significantly to vertical ocean carbon flux (Alldredge, 1976; Sato et al.,  
393 2003; Luo et al., 2022). The high importance of appendicularians in contributing to plankton  
394 community structure in intermittent upwelling systems further advances the body of literature  
395 emphasizing the often-overlooked importance of gelatinous plankton, and specifically,  
396 appendicularians. Protists are the prototypical constituent of the microbial loop (Azam et al., 1983;  
397 Williams and Ducklow, 2019; Glibert and Mitra, 2022) and their importance in generating plankton  
398 community structure at NH is not only a robust confirmation of high microbial loop activity but may  
399 also reflect the consumption of protists by appendicularians and *Oithona* copepods. These faunal  
400 patterns are consistent with the importance of sampling depth and the on-shelf/off-shelf variable in  
401 the NH co-occurrence model, as deeper off-shelf waters tend to be more oligotrophic and favorable  
402 for heightened microbial activity (Azam et al., 1983; Williams and Ducklow, 2019; Glibert and  
403 Mitra, 2022).

404  
405 In contrast to the variables influencing plankton community structure at NH, variation in plankton  
406 co-occurrences at TR was influenced most strongly by upwelling and chl *a*, both indicative of a  
407 system dominated by new productivity with relatively reduced importance of the microbial loop, and  
408 generally shorter trophic pathways (Rykaczewski and Checkley, 2008; Jacox et al., 2018). While the  
409 positive effect of chl *a* on predicted plankton co-occurrence increased almost linearly across the  
410 range of observed chl *a* values, predicted co-occurrence increased with the cumulative 10-d CUTI  
411 only up to a value of  $\sim 20 \text{ m}^{-3} \text{ s}^{-1}$  before dropping off. This non-linear relationship may be due to an  
412 imbalance of upwelling and relaxation events whereby too much and continuous upwelling lead to  
413 advective loss of plankton off the shelf (Largier et al., 2006; Kudela et al., 2008). Sampling year was  
414 also an important driver on the TR line where both upwelling strength and chl *a* were much higher in  
415 2018 compared to 2019. Northern California upwelling and chl *a* levels in 2018 and 2019 have been  
416 reported as average and slightly below average, respectively (Thompson et al., 2018, 2019); however,  
417 our measurements reveal larger differences. At TR, cumulative CUTI was much higher in 2018  
418 (winter =  $13.8 \text{ m}^{-3} \text{ s}^{-1}$ ; summer =  $22.3 \text{ m}^{-3} \text{ s}^{-1}$ ) relative to 2019 (winter =  $3.3 \text{ m}^{-3} \text{ s}^{-1}$ ; summer =  $6.2 \text{ m}^{-3}$   
419  $\text{s}^{-1}$ ). This interannual difference in CUTI likely also led to the much higher chl *a* levels observed in  
420 2018 relative to 2019 ( $> 45 \mu\text{g l}^{-1}$  in 2018 vs  $7.5 \mu\text{g l}^{-1}$  in 2019). Considering that CUTI and chl *a*  
421 were both important predictors in the TR model, these large differences between 2018 and 2019  
422 likely explain why the 'year' variable was also important and why 2018 predicted higher co-  
423 occurrences. Other variables that were important in driving plankton co-occurrences on the TR and  
424 NH lines were temperature and oxygen. Both are key drivers in structuring pelagic plankton  
425 ecosystems, through physiological effects that can impact predator-prey interactions, as well as  
426 physical discontinuities that can constrain plankton movement (Rutherford et al., 1999; Rebstock,  
427 2003; Brodeur et al., 2019). Temperature and oxygen are also two of the variables most affected by  
428 climate change (Chan et al., 2019; Bograd et al., 2022; Smith et al., 2022).

429  
430 In a strong (i.e., continuous) upwelling environment (TR), a reduction in upwelling and resulting  
431 lower chl *a* lead to a reversal of the prevailing on-shelf/off-shelf pattern of co-occurrence, while in an  
432 already lower upwelling strength environment (i.e., intermittent upwelling regime; NH), a further  
433 reduction of upwelling leads to little change in on-shelf/off-shelf co-occurrence patterns. The larger  
434 effect on plankton co-occurrences in the strong upwelling environment is consistent with the  
435 expectation that the established trophic web is reliant on the input of nutrients through upwelling and  
436 subsequent phytoplankton blooms (Barth et al., 2007; Bograd et al., 2009; Jacox et al., 2018). In an  
437 intermittent upwelling environment, where we found several microbial loop taxa to be important in

438 predicting co-occurrences, the established trophic web (including a protist - *Oithona* -  
439 appendicularian link) is less reliant on nutrient input from upwelling (Azam et al., 1983; Williams  
440 and Ducklow, 2019), thus a further reduction in upwelling would be expected to have a smaller  
441 effect.

442  
443 It is well established that the microbial loop is an important part of many marine ecosystems  
444 (Wilkerson et al., 1987; Taylor and Landry, 2018; Williams and Ducklow, 2019; Thompson et al.,  
445 2021; Glibert and Mitra, 2022). Recent establishment of the mixoplankton paradigm—ubiquitous  
446 microbes that survive on phototrophy and phagotrophy synergistically—has had far reaching ripple  
447 effects (Flynn et al., 2019; Glibert and Mitra, 2022). Long considered minor players, mixotrophs are  
448 now known to comprise large parts of the microbial loop and are of high importance in the global  
449 plankton trophic web. Nonetheless, the role of the microbial loop in shaping overall plankton  
450 community structure, particularly in the context of variable environmental conditions, is not well  
451 understood. Several comparative studies have investigated the relative carbon contributions of broad  
452 taxa to new productivity and the microbial loop (Tilstone et al., 1999; Vargas et al., 2007; Landry et  
453 al., 2012; Taylor et al., 2015). For example, in a productive coastal upwelling region in the Humboldt  
454 Current, the microbial loop was found to channel a large portion of the energy flow, while new  
455 productivity contributed only a small portion of the transferred carbon (Vargas et al., 2007).  
456

457 Our in-situ plankton imagery demonstrates that the role of the microbial loop in driving  
458 mesoplankton community structure is more evident in intermittent upwelling regimes relative to  
459 continuous upwelling regions. While areas dominated by upwelling and high nutrient input also  
460 include microbial constituents, new productivity plays a larger role in structuring the plankton  
461 community. Here, large changes in upwelling result in sharp spatial changes to plankton community  
462 structure. In intermittent or low upwelling areas, microbial loop constituents are more important  
463 drivers of overall plankton community structure, resulting in a more temporally stable plankton  
464 community structure, even in the face of changes to upwelling strength.  
465

466 Complexities of nutrient-plankton interactions, including the microbial loop, are often not well  
467 represented in models, and need refining, especially with regard to adequately including mixotrophy  
468 (Ratnarajah et al., 2023). Updating these models becomes especially urgent in the uncertain future  
469 ocean.

470  
471 **4.2 Plankton community structure under future climate change**  
472

473 Recently the NCC has been subject to disruptive marine heatwaves, affecting multiple trophic levels  
474 (Cavole et al., 2016; Oliver et al., 2018; Fennie et al., *in revision*) and reducing biodiversity on basin  
475 scales (Smale et al., 2019; Smith et al., 2022). Unfortunately, such extreme events are also predicted  
476 to become more prevalent in the future (Jacox et al., 2022). Marine heatwaves can lead to changes in  
477 plankton and nekton community structure (Brodeur et al., 2019) and to die-offs in seabirds, marine  
478 mammals, and kelp (Smith et al., 2022). Simultaneously, deeper and stronger stratification will result  
479 in lower nutrient supply to surface waters, with a resulting impact on food web structure—i.e., a shift  
480 to smaller plankters that rely to a greater extent on microbial-based nutrient recycling (Behrenfeld  
481 and Boss, 2013)—generating longer, less-efficient food chains. Meanwhile, changing wind patterns  
482 are projected to intensify upwelling in the NCC, and to decrease upwelling-favorable winds in the  
483 central and southern California Current Ecosystem (Buil et al., 2021). Our findings suggest that as  
484 these changes in wind patterns lead to shifts in intermittent and continuous upwelling regimes,  
485 current continuous upwelling regions will likely transition to a plankton community structure that is  
486 driven more by microbial loop constituents, and current intermittent upwelling regions will likely

487 transition to systems dominated by new productivity. Such fundamental changes would likely have  
488 important consequences for energy transport through the trophic web to top predators and fisheries.  
489

490 **4.3 Conclusions**

491  
492 Collection and analysis of a vast dataset of in situ underwater plankton imagery (>1.1 billion  
493 plankton images) revealed substantial differences in the way that plankton community structure is  
494 driven under intermittent and continuous upwelling regimes. A reduction of upwelling strength in a  
495 continuous upwelling regime induced large scale changes in plankton community structure that  
496 affected on-shelf and off-shelf taxa co-occurrences, while in an intermittent upwelling regime, more  
497 strongly influenced by microbial loop constituents, a reduction of upwelling strength had little effect  
498 on plankton community structure. We thus hypothesize that high microbial loop activity enhances the  
499 resilience of plankton community structure to climate change induced shifts in upwelling strength.  
500 This concept is consistent with the mixotrophy paradigm in which the base of the microbial loop—the  
501 mixotrophs—are better adapted to a changing ocean (e.g., changing nutrient availability) than pure  
502 auto-, or heterotrophs, due to their ability to survive on either (Glibert and Mitra, 2022).

503

504

505 **5 Figure legends**

506  
507 Figure 1. ISIS transects along the Newport Hydrographic (NH) and Trinidad Head (TR) lines (black  
508 solid line) where sampling occurred in winter and summer 2018 and 2019. Chlorophyll *a* from Aqua  
509 Modis ocean color on July 10, 2018 shows the often higher productivity in the northern California  
510 part of the Northern California Current, where the shelf is narrower than farther north at the NH Line  
511 (depth contours in solid grey lines at 50m, 100m, 200m, 1000m, 2000m). Light grey pixels indicate  
512 non-available data from Aqua Modis.

513

514 Figure 2. High spatial distribution profiles (e.g., here *Oithona* sp., left panel – shelf delineated as a  
515 grey polygon) are correlated with all other taxa and led to correlograms that depict co-occurrence  
516 amongst taxa (right panel). In this example, the on-shelf portion of the left panel would result in one  
517 correlogram, and the off-shelf part in another. The black box shows *Oithona* sp. co-occurrence with  
518 other taxa (blue hues indicating negative correlation and red hues positive correlation, grey boxes are  
519 correlations that are not significant at  $p < 0.01$ ), while other taxa correlations above and below depict  
520 correlations of the remainder of the plankton community on the transect.

521

522 Figure 3. ISIS images of key taxa in the northern California Current. (A) Primary producers and  
523 protists; (B-C) crustaceans (D) cnidarians, ctenophores, and echinoderms; (E) heteropods and  
524 pteropods; (F) chaetognaths and polychaetes; (G) pelagic tunicates; (H) larval fishes.

525

526 Figure 4. Temperature (A), Salinity (B), Density (C), Oxygen (D) and Chlorophyll *a* (chl *a*, E) across  
527 the Newport Hydrographic (NH) and Trinidad Head (TR) transects in winter and summer 2018.  
528 Winter sampling on the NH and TR shown here was carried out February 16 and 21, respectively,  
529 while summer sampling was carried out on July 10 and 7, respectively. Note that Chl *a* is plotted in  
530  $\log(x+1)$  due to the values ranging from 0.01 to 45  $\mu\text{g l}^{-1}$ . Shelf indicated in dark grey.

531

532 Figure 5. Temperature (A), Salinity (B), Density (C), Oxygen (D) and Chlorophyll *a* (chl *a*, E) across  
533 the Newport Hydrographic (NH) and Trinidad Head (TR) transects in winter and summer 2019.  
534 Winter sampling on the NH and TR shown here was carried out on March 6 and 8, respectively,  
535 while summer sampling was carried out on July 23 and 18, respectively. Shelf indicated in dark grey.

536  
537 Figure 6. Cumulative Coastal Upwelling Transport Index (CUTI) over 10 d prior to sampling at the  
538 Newport Hydrographic (NH) and Trinidad Head (TR) lines.  
539  
540 Figure 7. T-S diagrams during summer and winter sampling (2018, 2019) along the Newport  
541 Hydrographic (NH), and Trinidad Head (TR) lines. Light grey numbers and dotted lines indicate  
542 isopycnals.  
543  
544 Figure 8. Co-occurrence of plankton taxa (y-axis) with all other taxa on the shelf (green) and off the  
545 shelf (red) along the Newport Hydrographic (NH) line. Vertical lines indicate taxa averages of co-  
546 occurrence as measured by spatial correlations. Stars indicate significant differences between on-,  
547 and off-shelf co-occurrence averages using Wilcoxon Rank Sum tests ( $p < 0.0001$ ).  
548  
549 Figure 9. Co-occurrence of plankton taxa (y-axis) with all other taxa on the shelf (green) and off the  
550 shelf (red) along the Trinidad Head line. Vertical lines indicate taxa averages of co-occurrence as  
551 measured by spatial correlations. Stars indicate significant differences between on-, and off-shelf co-  
552 occurrence averages using Wilcoxon Rank Sum tests ( $p < 0.0001$ ).  
553  
554 Figure 10. Coefficients of variation of plankton taxa co-occurrences along the Newport Hydrographic  
555 (NH) and Trinidad Head (TR) lines.  
556  
557 Figure 11. Plankton taxa co-occurrence as a function of the 10-d cumulative Coastal Upwelling  
558 Transport Index (CUTI) along the Newport Hydrographic (NH) and Trinidad Head (TR) lines;  
559 Wilcoxon test (ns = not significant, \*\*  $p < 0.001$ ).  
560  
561 Figure 12. Top ten variables in the Random Forests models of plankton cooccurrence at the Newport  
562 Hydrographic (NH) and Trinidad Head (TR) lines, ordered by relative variance explained (variance  
563 scaled to 100% based on the most important variable).  
564  
565 Figure 13. Partial dependence plots for the top 10 most important variables in the Random Forests  
566 models of plankton co-occurrence on the Newport Hydrographic (NH) and Trinidad Head (TR) lines.  
567 Note the differing y-axis scale between NH and TR  
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## 6 Tables

Table 1: Variables used in Random Forests modeling included biotic and abiotic environmental variables (1-14) and taxa concentrations derived from underwater imaging (15-83).

	Name	Unit	Name	Unit
1	Shelf (On/Off)	-	43	detritus
2	Distance	km	44	diatoms
3	Depth	m	45	echinoderm_brachiolaria
4	Year (2018 / 2019)	-	46	echinoderm_pluteus
5	Season (winter / summer)	-	47	fish_clupeiformes
6	Cumulative CUTI (10 day)	$m^{-3} s^{-1}$	48	fish_flatfish
7	Temperature	°C	49	fish_long_slender
8	Salinity	-	50	fish_myctophid
9	Oxygen	$ml l^{-1}$	51	fish_sebastes
10	Chlorophyll <i>a</i>	$\mu g l^{-1}$	52	fish_unknown
11	Density	$kg m^{-3}$	53	foraminifera
12	Geostrophic Dynamic Height Anomaly	$m^2 s^{-2}$	54	hydromedusae_anthomedusae_other
13	Mixed layer depth	m	55	hydromedusae_anthomedusae_velella
14	Brunt Vaisala Frequency squared	$rad^2 s^{-2}$	56	hydromedusae_leptomedusae_eutonina
15	appendicularians	$ind. m^{-3}$	57	hydromedusae_leptomedusae_clytia_mitrocoma
16	chaetognaths	"	58	hydromedusae_leptomedusae_other
17	copepod_calanoid_calanus	"	59	hydromedusae_narcomedusae_aegina
18	copepod_calanoid_diaptomoidea	"	60	hydromedusae_narcomedusae_other
19	copepod_calanoid_mesocalanus	"	61	hydromedusae_narcomedusae_solmaris
20	copepod_calanoid_metridia	"	62	hydromedusae_narcomedusae_solmundella
21	copepod_calanoid_other	"	63	hydromedusae_other
22	copepod_calanoid_paracalanidae	"	64	hydromedusae_trachymedusae_aglantha
23	copepod_calanoid_paraeuchaeta	"	65	hydromedusae_trachymedusae_aglaura
24	copepod_calanoid_pseudocalanus	"	66	hydromedusae_trachymedusae_arctapodema
25	copepod_carcass	"	67	hydromedusae_unknown
26	copepod_cyclopoid_oithona	"	68	phytoplankton_diatom_chain
27	copepod_cyclopoid_oithona_eggs	"	69	polychaete
28	copepod_eucalaniid	"	70	polychaete_larvae
29	copepod_other	"	71	protist_acantharia
30	copepod_poecilostomatoid	"	72	protist_noctiluca
31	crustacean_amphipods	"	73	protist_other
32	crustacean_megalopae	"	74	protist_radiolarian_other
33	crustacean_ostracod	"	75	pteropod
34	crustacean_other	"	76	pyrosome
35	crustacean_shrimp_caridean	"	77	siphonophore_calycophoran_abylidae
36	crustacean_shrimp_euphausiid	"	78	siphonophore_calycophoran_muggiaeae
37	crustacean_shrimp_molt	"	79	siphonophore_calycophoran_sphaeronectes
38	crustacean_shrimp_mysids	"	80	siphonophore_other
39	crustacean_zoea	"	81	siphonophore_physonect
40	ctenophore_beroe	"	82	tunicate_doliolid
41	ctenophore_cydippid	"	83	tunicate_salp
42	ctenophore_lobate	"		

588

589 **7 Conflict of Interest**

590 The authors declare that the research was conducted in the absence of any commercial or financial  
591 relationships that could be construed as a potential conflict of interest.

592 **8 Author Contributions**

593 MSS performed analyses and wrote the initial manuscript; SS, RKC, KRS, and MSS conceptualized  
594 hypotheses and research questions; SS, RKC, and KRS designed the study, sampling program, and  
595 wrote grant proposals; MSS, RKC, and KRS collected data; all authors interpreted the data, discussed  
596 the results, contributed to the critical revision of the manuscript and figures, and approved the final  
597 version.

598 **9 Funding**

599 Support for this study was provided by NSF OCE-1737399, NSF OCE-2125407, and NSF  
600 XSEDE/ACCESS OCE170012.

601 **10 Acknowledgments**

602 We thank our collaborators Chris Sullivan and Dominic Daprano (both at Oregon State University)  
603 for invaluable support with processing the vast quantity of data presented here. We also thank Kelsey  
604 Swieca and Christian Briseño-Avena for their help creating the sCNN training library. Current and  
605 former members of the OSU Plankton Ecology Lab at the Hatfield Marine Science Center helped  
606 collect the data presented here on the four cruises, we thank them for their efforts – Jami Ivory,  
607 Christian Briseño-Avena, Kelsey Swieca, Miram Gleiber, H. Will Fennie, Megan Wilson, and Keely  
608 Axler. The professionalism of the officers and crews of RV *Sikuliaq* (Winter 2018 and 2019), RV  
609 *Sally Ride* (Summer 2018) and RV *Atlantis* (Summer 2019) enabled this project, and we are grateful  
610 to them. We thank NSF XSEDE/ACCESS and specifically staff Manu Shantharam at the San Diego  
611 Supercomputing Center as well as Sergiu Sanlievici at the Pittsburgh Supercomputing Center for  
612 their support with classifying the image data presented here.

613

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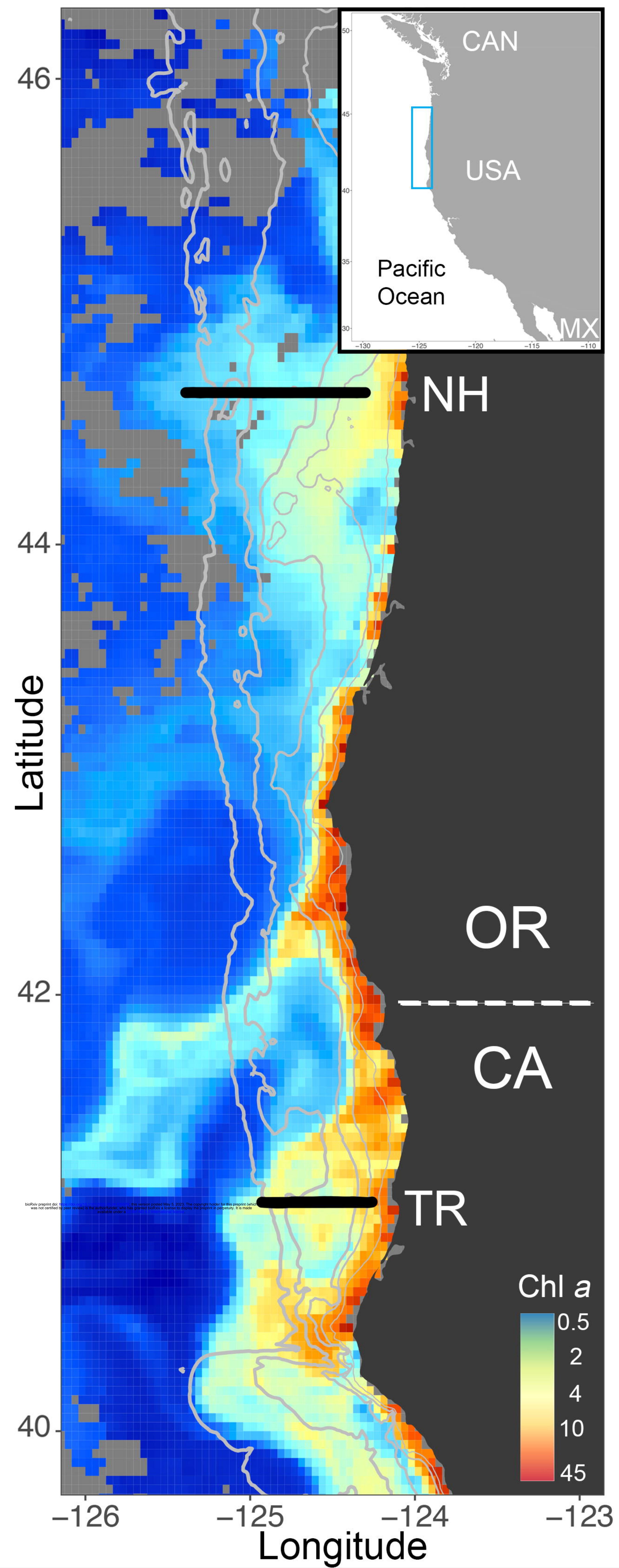
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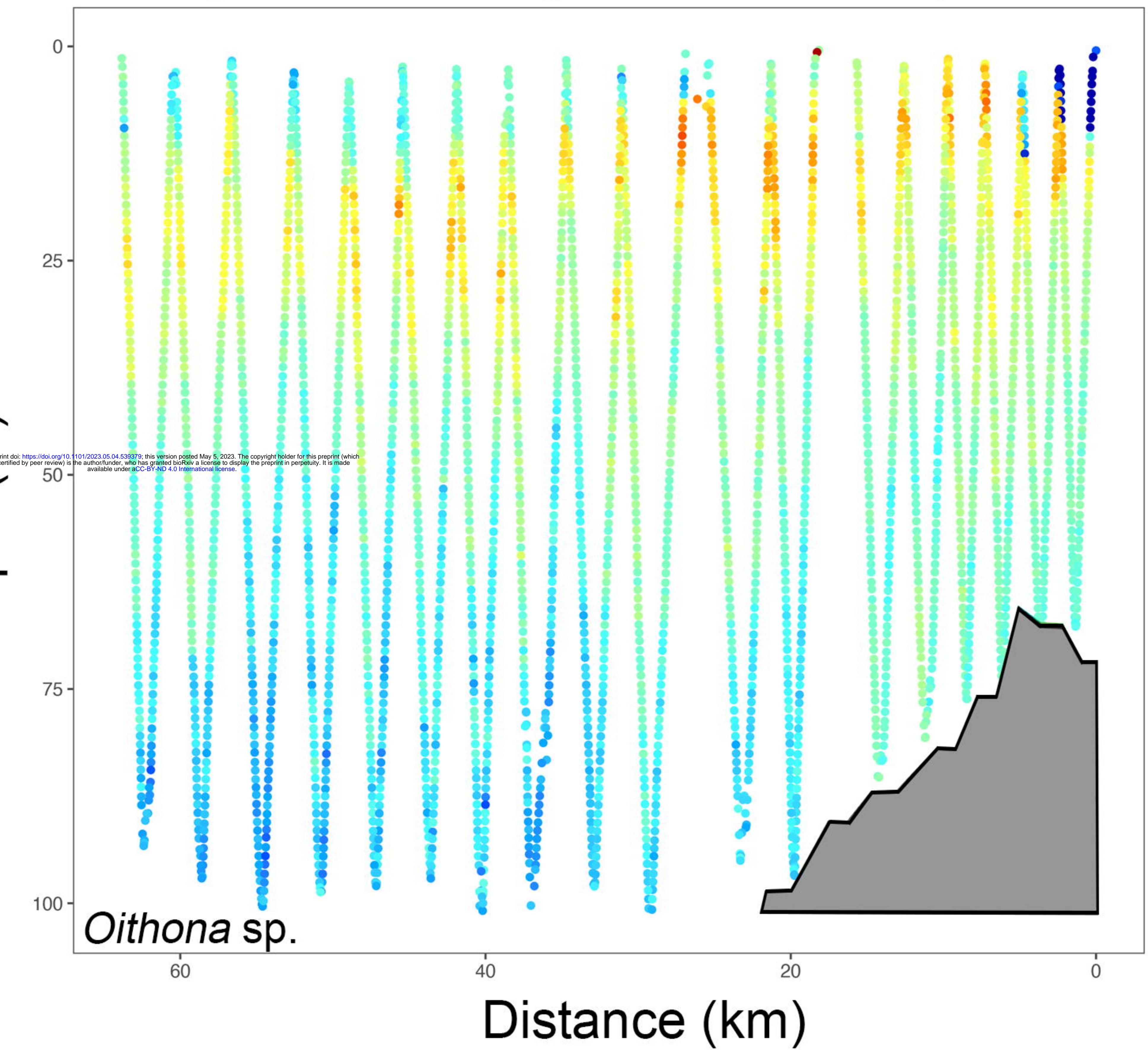
1110 **12 Data Availability Statement**

1111 Data are available at NSF’s BCO-DMO <https://www.bco-dmo.org/project/743417> as well as the R2R  
1112 program: <https://www.rvdata.us/search/cruise/SKQ201804S>,  
1113 <https://www.rvdata.us/search/cruise/SR1810>, <https://www.rvdata.us/search/cruise/AT42-13>, and  
1114 <https://www.rvdata.us/search/cruise/SKQ201903S>.

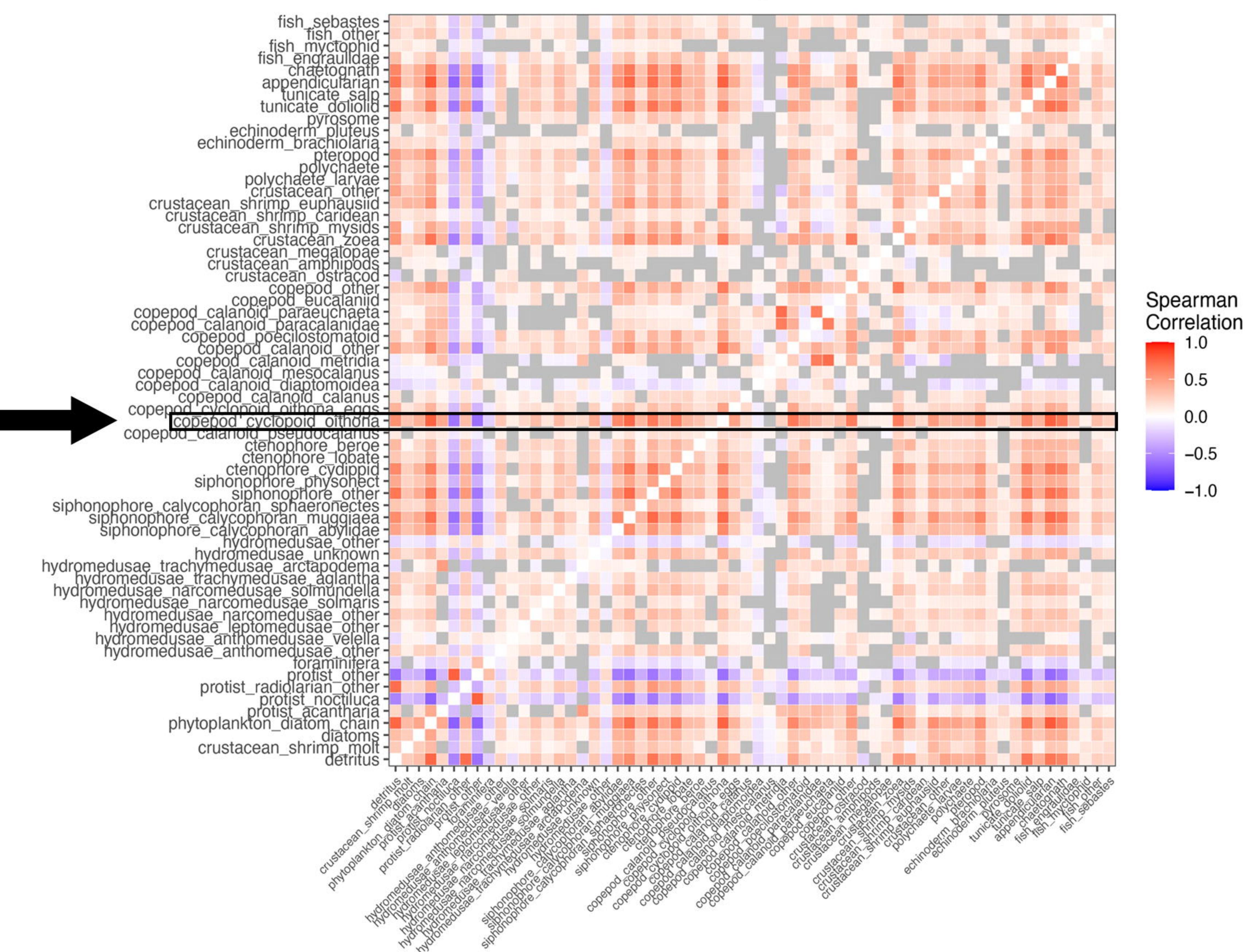


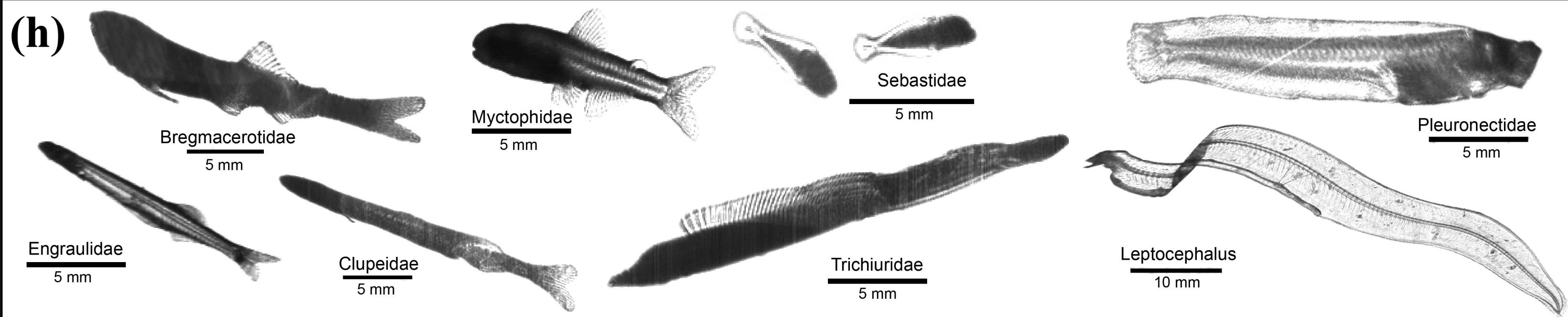
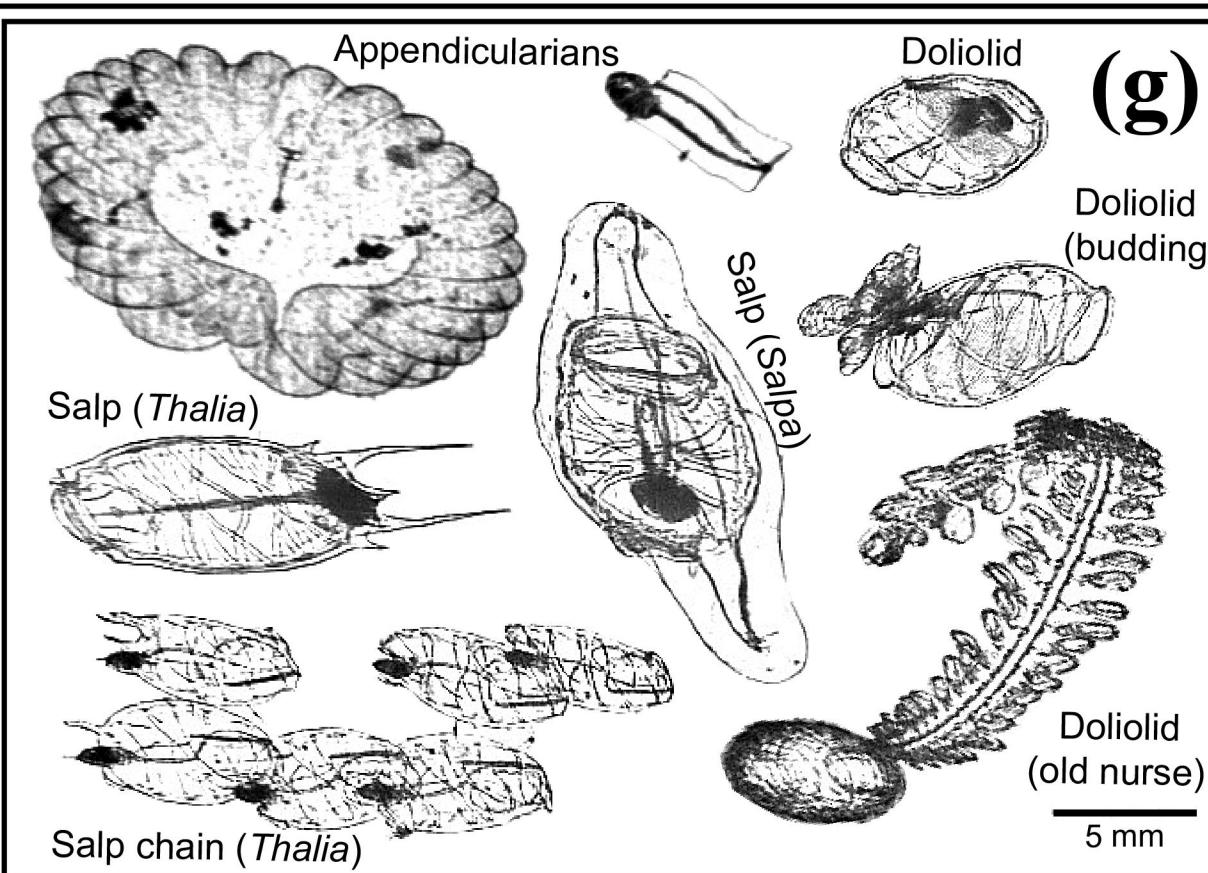
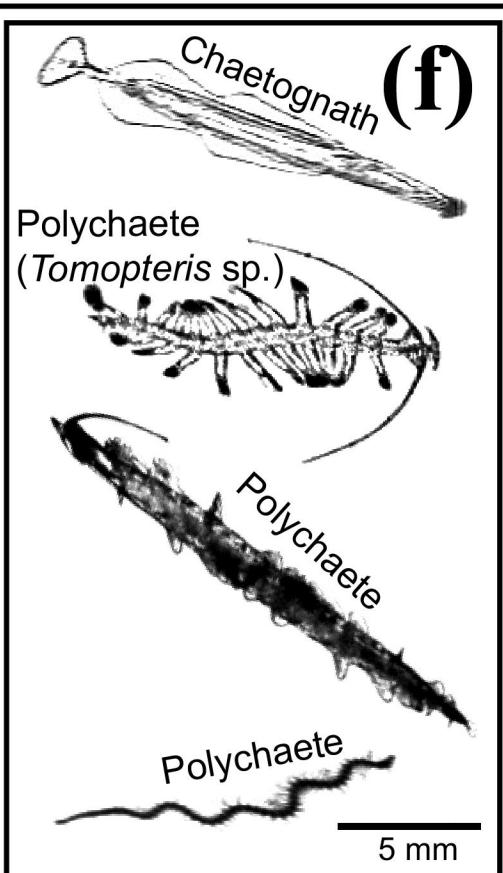
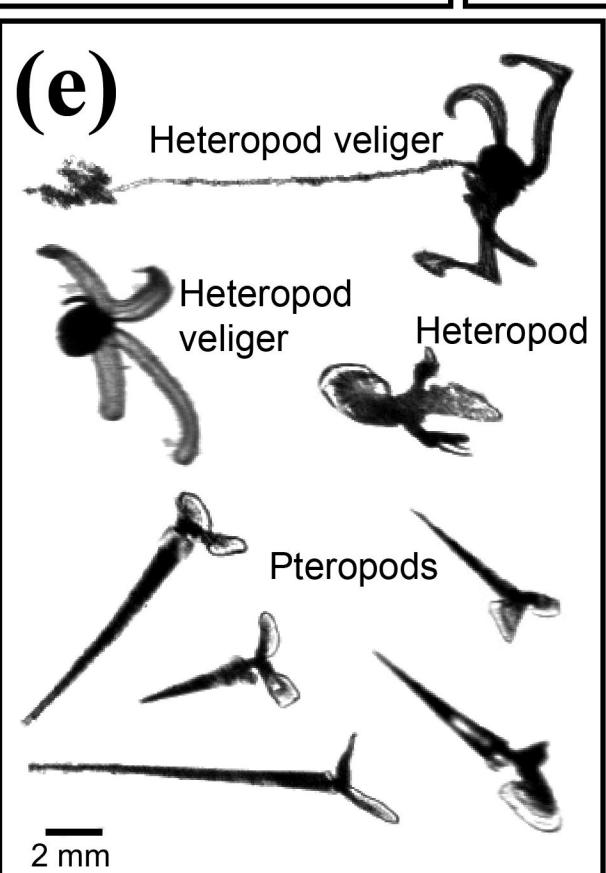
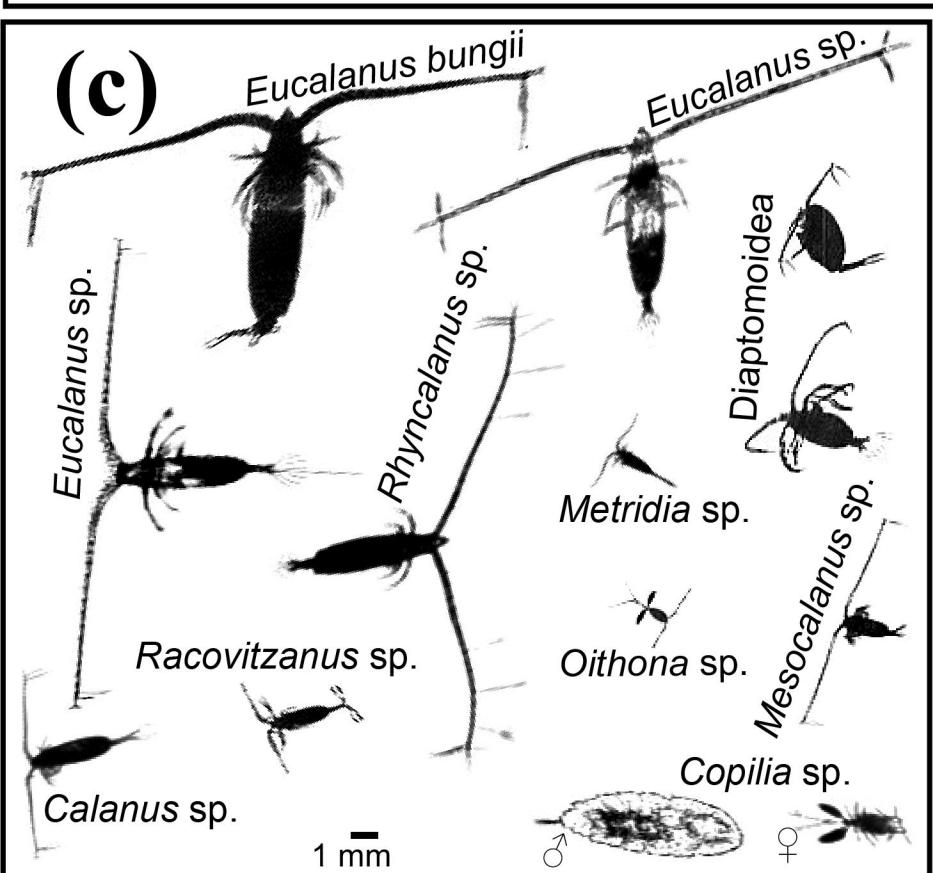
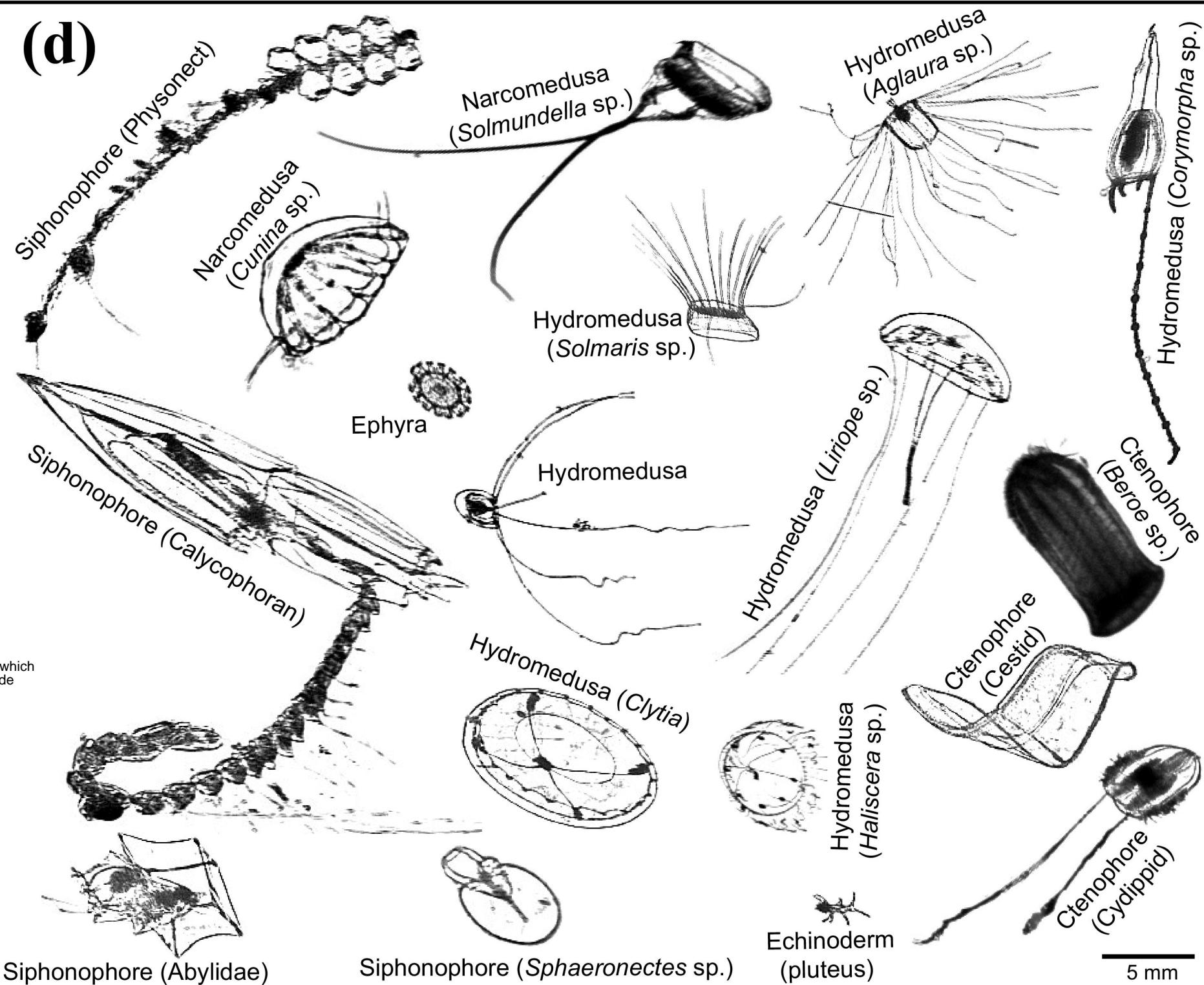
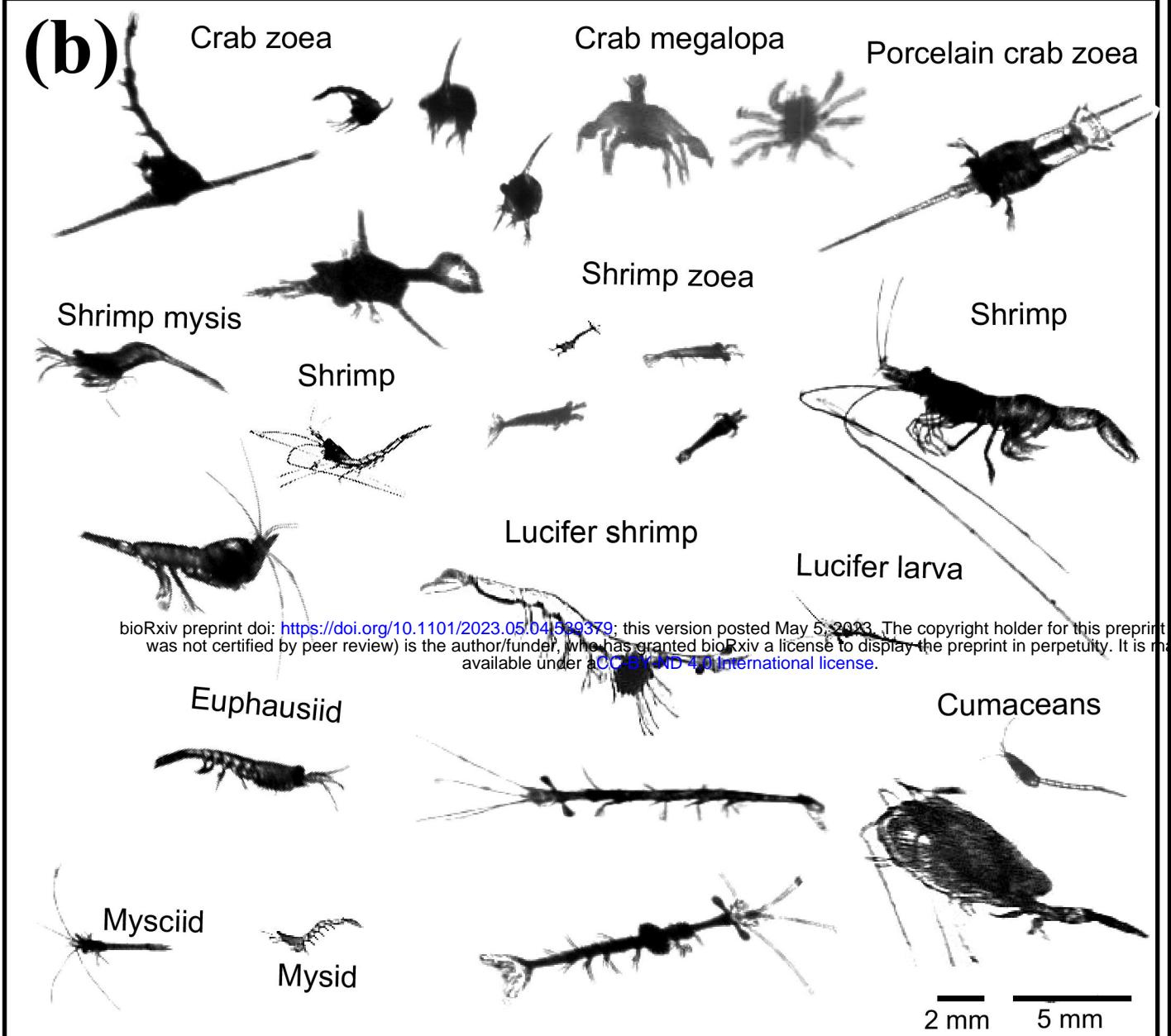
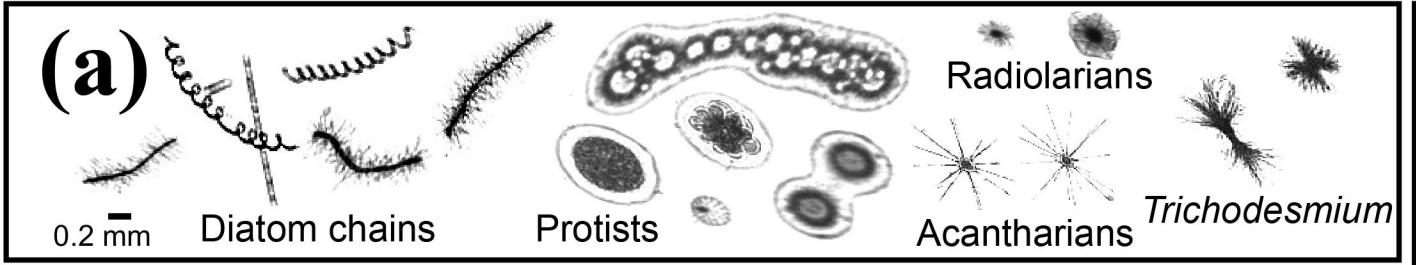
# Single taxon high resolution profiles


Depth (m)




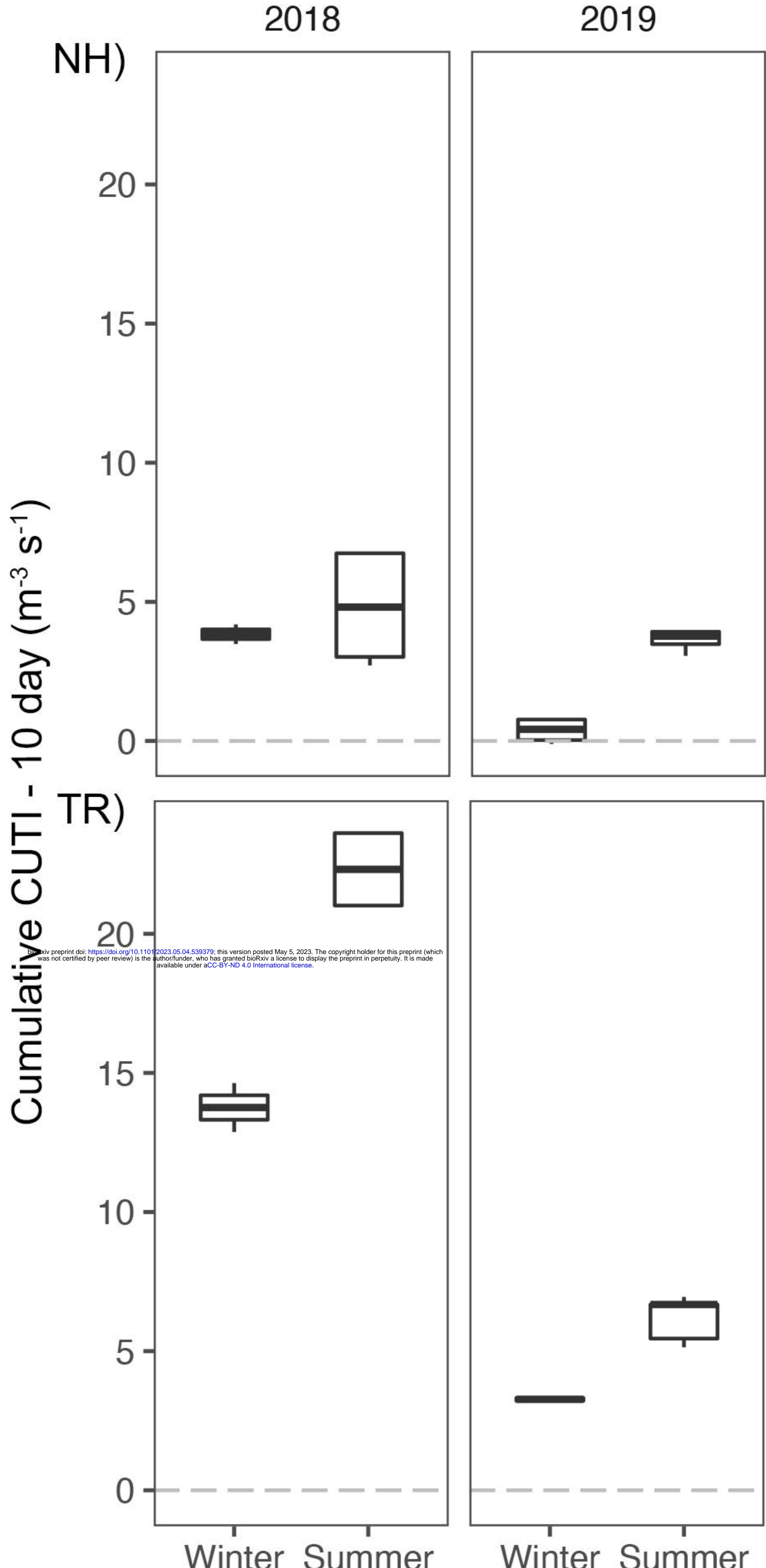
# Community structure

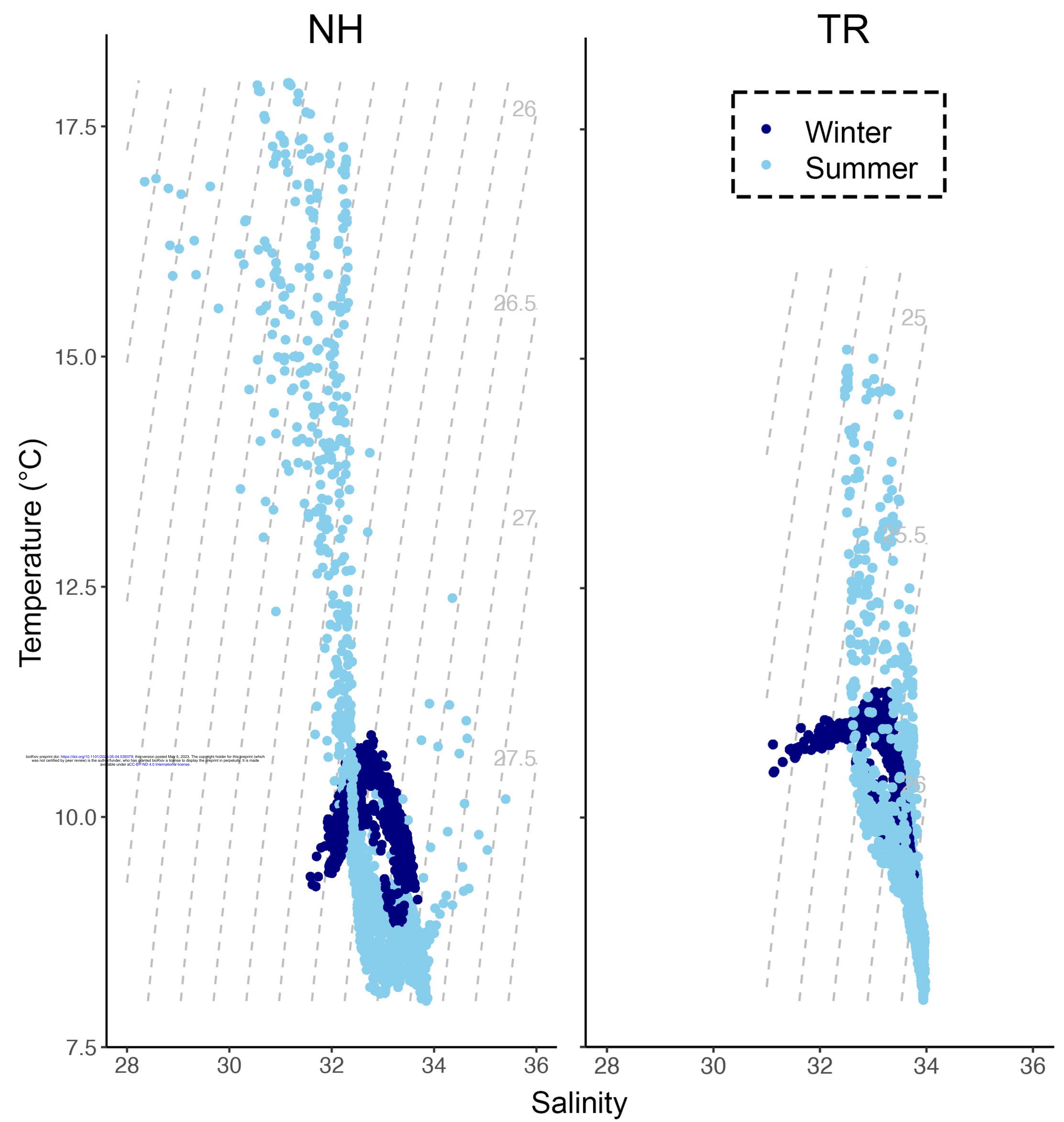












2018


Winter

Summer

2019

Winter

Summer



2018


Winter

Summer

2019

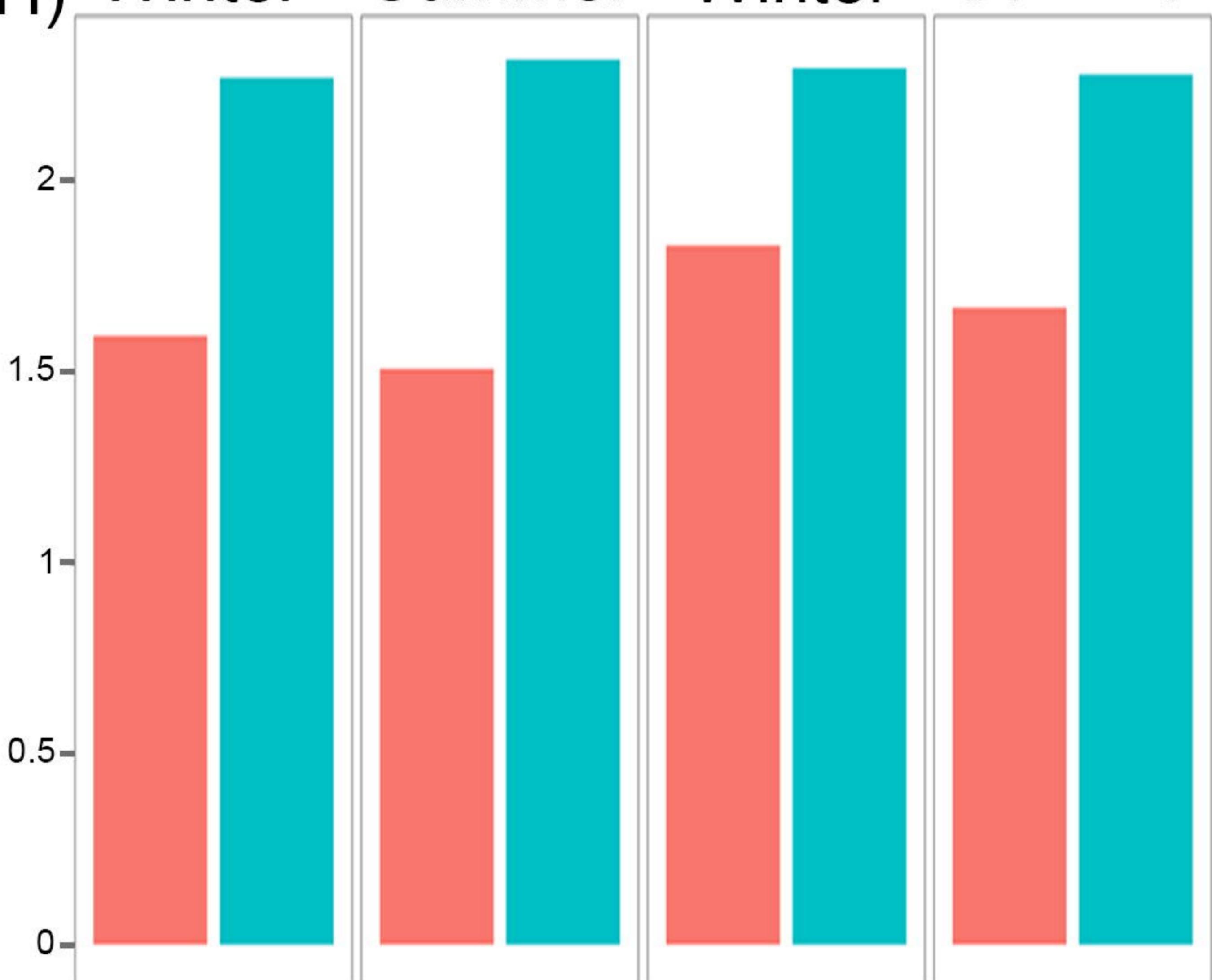
Winter

Summer



2018 2019  
NH) Winter Summer Winter Summer

Coefficient of variation of co-occurrence

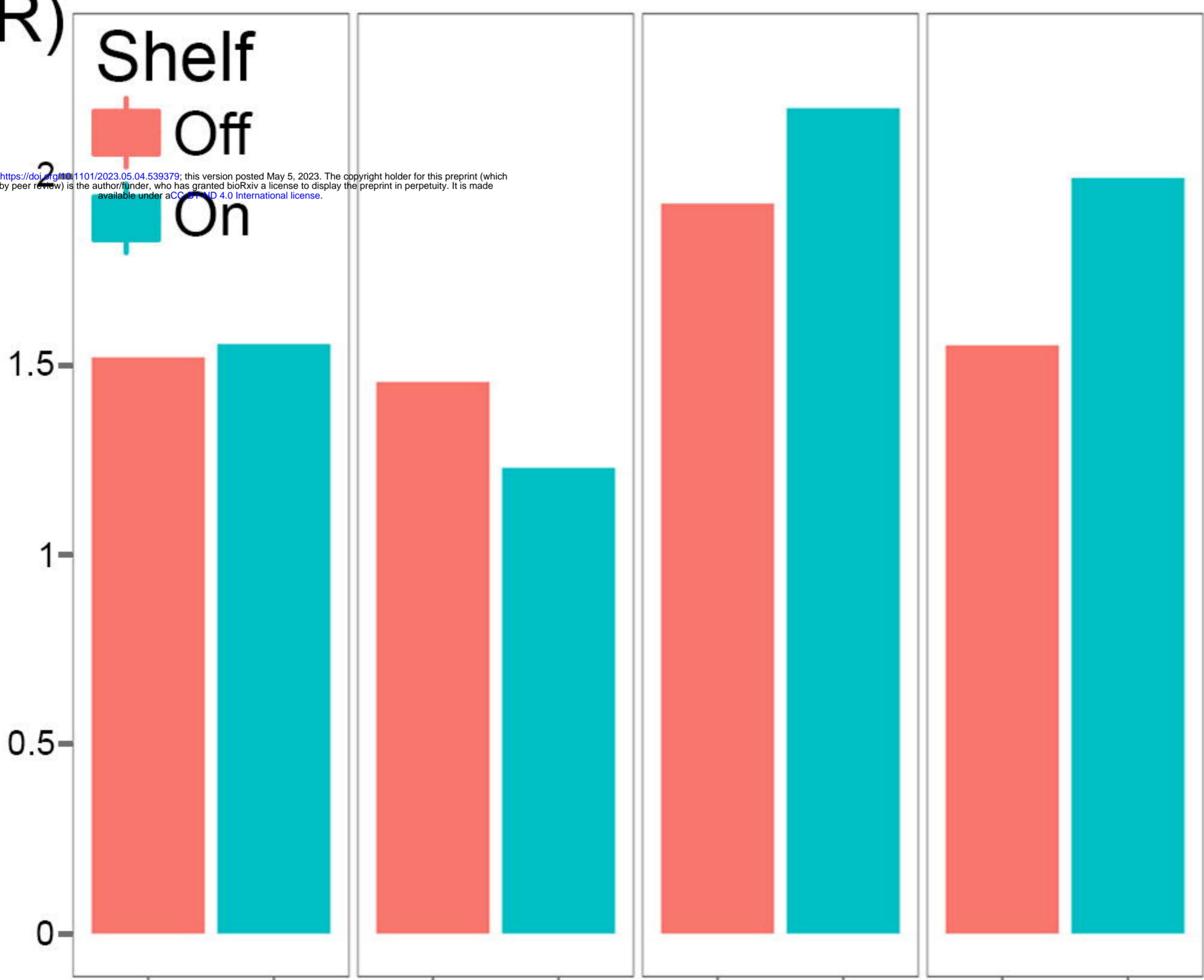


TR)

Shelf  
Off  
On

bioRxiv preprint doi: <https://doi.org/10.1101/2023.05.04.539379>; this version posted May 5, 2023. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted bioRxiv a license to display the preprint in perpetuity. It is made available under aCC-BY-ND 4.0 International license.

Coefficient of variation of co-occurrence



Shelf categories

0.16- Wilcoxon:  $y = 0.069 + 0.0004 x$ ,  $R^2 = 0.04$   $p = \text{ns}$

$$y = 0.062 + 0.002 x, R^2 = 0.39 \quad p = **$$

