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1 **Title: Spatio-temporal patterns of multi-trophic biodiversity and food-web characteristics**  
2 **across a river catchment**

3

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26 **Abstract**

27

28 Accurate characterisation of ecological communities with respect to their biodiversity and food-  
29 web structure is essential for conservation. However, combined empirical study of biodiversity  
30 and multi-trophic food webs at a large spatial and temporal resolution has been prohibited by the  
31 lack of appropriate access to such data from natural systems. Here, we assessed biodiversity and  
32 food-web characteristics across a 700 km<sup>2</sup> riverine network through time using environmental  
33 DNA. We find contrasting biodiversity patterns, with richness ( $\alpha$ -diversity) of fish increasing  
34 towards downstream positions within the catchment, while freshwater bacteria and invertebrates  
35 having an invariant and minimal decrease in richness, respectively, with downstream position.  
36 Food-web characteristics, such as link density and nestedness, however, were relatively  
37 conserved across space, but varied over season. Patterns of biodiversity across major taxonomic  
38 groups are thus not directly scalable to food-web structures at the same spatial and temporal  
39 scales, indicating that effective conservation measures must consider them jointly.

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## 40 **Introduction**

41

42 The study of biodiversity patterns<sup>1-3</sup> and the characterisation of food-web structures<sup>4,5</sup> are  
43 essential, yet often disconnected goals in ecology. Understanding these patterns is not only of  
44 fundamental interest, but also needed to predict stability, functioning and resilience of natural  
45 ecosystems and to bend the curve of biodiversity loss in the context of anthropogenic pressures  
46 including contemporary global change<sup>6</sup>.

47

48 Studies on biodiversity predominantly focus on analyses of  $\alpha$ -,  $\beta$ - and  $\gamma$ -diversity and possible  
49 underlying fundamental drivers of their spatial or temporal patterns<sup>7</sup>. Freshwater rivers are  
50 highly spatially structured systems<sup>8-10</sup> in which theoretical and empirical studies have identified  
51 characteristic patterns of biodiversity for specific groups. For example, fish  $\alpha$ -diversity has been  
52 found to increase with distance downstream<sup>11</sup>, whereas headwaters often show high endemic  
53 bacterial species richness<sup>12</sup>. Aquatic invertebrate biodiversity exhibits more complicated overall  
54 patterns with disproportionately high biodiversity being found in headwaters<sup>13</sup> and a significant  
55 increase in biodiversity linked to catchment size<sup>14</sup>. However, these group-specific biodiversity  
56 patterns have been mostly studied in isolation from one another, although species are present  
57 within the same system and trophically interact with each other. Indeed, recent theoretical work  
58 shows that contrasting patterns driven by species' resource competition are possible<sup>15</sup>. Therefore,  
59 to ensure optimal strategies for conservation and understanding of biodiversity patterns across  
60 different organismal groups, an ensemble approach integrating major taxonomic and trophic  
61 groups is crucial to reveal how species are linked through trophic interactions<sup>16</sup>.

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63 Trophic interactions and food webs by definition encompass multiple groups of organisms.  
64 Individual freshwater food webs are well-resolved<sup>17</sup>, and often exhibiting distinct features, such  
65 as highly nested structures<sup>18</sup> and prevalent omnivory<sup>17,19</sup>. Nevertheless, food-web studies often  
66 have a localised perspective due to methodological limitations of sampling food-web interactions  
67 and organismal occurrence in a standardized and comparable manner across different places and  
68 organismal groups<sup>20–22</sup>. Due to the same reason, these studies also tend to focus on simple spatial  
69 and environmental gradients<sup>23</sup> or temporal change<sup>24</sup> when spatio-temporal influences should be  
70 considered in conjunction<sup>25,26</sup>. This is particularly problematic in freshwater riverine ecosystems,  
71 that are characterised by a high spatio-temporal structure: they exhibit characteristic spatial  
72 structures, and have strong seasonal variations driven by changing abiotic conditions<sup>27</sup> and  
73 pronounced life-cycle changes of key taxa inhabiting these systems. The variation in dynamics  
74 over the course of a year remains a significant gap in our understanding of freshwater food  
75 webs<sup>17,28</sup>.

76  
77 To effectively conserve riverine biodiversity, we must encompass spatio-temporal variation of  
78 multiple trophic levels to understand the underlying dynamics of both biodiversity patterns and  
79 food-web characteristics<sup>4,25,26</sup>. In particular, molecular monitoring techniques may now provide a  
80 suitable solution to break through the above-mentioned methodological constraints caused by  
81 sampling based primarily on species sight or capture. Environmental DNA, or eDNA, is the  
82 collection of DNA extracted from an environmental sample such as water, air or sediment<sup>29</sup>. By  
83 collecting eDNA we can screen samples for multiple taxonomic groups via metabarcoding<sup>30</sup>,  
84 thereby creating a biodiversity assessment suitable for food-web reconstruction.

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86 Here, we use eDNA metabarcoding to assess patterns of biodiversity and reconstruct local food  
87 webs via a metaweb-based approach<sup>31</sup>. The metaweb approach is suitable to capture food-web  
88 patterns based on taxa co-occurrence data<sup>24,32</sup> in both terrestrial and aquatic systems. We used  
89 high-throughput sequencing and a multi-marker approach to examine three taxonomically  
90 relevant groups, namely fish (via the 12S barcode region), invertebrates (cytochrome *c* oxidase I  
91 - COI) and bacteria (16S) in a large-scale river network over the course of three seasons (spring,  
92 summer and autumn). This approach allowed us to test for association of biodiversity patterns  
93 and food-web structures with network location and seasonal change. We found contrasting  
94 effects on biodiversity patterns and food-web structure from spatial and temporal influences,  
95 respectively, providing insight into the underlying changing ecosystem dynamics and indicating  
96 that effective and targeted conservation measures must consider them jointly.

97

## 98 **Results**

99

### 100 *Data collection and community construction*

101 We collected water samples from the upper Thur catchment, Switzerland, which covers  
102 approximately 700 km<sup>2</sup> and is made up of three sub-catchments: River Thur, Necker and Glatt.  
103 Seventy-three field sites were selected to allow for maximum coverage across the catchment  
104 area, comprising of a broad size range of upstream drainage sizes (i.e., the drainage area size  
105 indicates the location of the site within the catchment: upstream sites having a small drainage  
106 area and lowland sites having a larger drainage, see Fig. 1). Water samples were filtered on site  
107 and DNA extracted in a specialist clean lab environment at Eawag, Switzerland. A total of 12.29  
108 million, 14.32 million and 14.02 million raw reads were produced from the 12S, COI and 16S

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109 libraries, respectively. After bioinformatic processing the average sequencing read depth per  
110 sample was: 43,176, 50,704 and 49,857 for 12S, COI and 16S, respectively. This included 159  
111 Zero-radius Operational Taxonomic Units (ZOTUs), 3179 ZOTUs and 11,320 ZOTUs for 12S,  
112 COI and 16S respectively (see Methods and Supplementary Information Table S1 for details on  
113 laboratory and bioinformatic analysis). For further analysis, ZOTUs were merged to genus level  
114 and only fish genera, invertebrate genera with an aquatic life stage and bacteria associated with  
115 freshwater were kept for further analysis (See Methods for further details). Analysis was  
116 performed on presence/absence data to merge the three libraries for the complete freshwater  
117 community and exclude a possible influence of uneven sample read depth generated from  
118 multiple markers (see also <sup>33</sup>).

119

120 To quantify biodiversity, we calculated  $\alpha$ -diversity (local richness) at genus level at each site and  
121 compared  $\beta$ -diversity (variation in community composition between sites) by using Jaccard  
122 dissimilarity. Jaccard dissimilarity was also partitioned into taxon replacement (turnover) and  
123 taxon loss (nestedness) components to assess the mechanisms contributing to the variation in  
124 community assemblage across the catchment.

125

126 To measure food webs and functional characteristics of the community, we constructed a  
127 metaweb based on known interactions of genera classified into different functional feeding  
128 groups (Fig. 2; see also Methods and Supplementary Information Table S2). We defined local  
129 food webs at each field site based on genera co-occurrence and the corresponding subset of  
130 interactions from the metaweb, to determine broad changes in the community over time and

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131 space. With this approach, variation in food-web structures and function feeding groups emerge  
132 from the spatio-temporal differences in genus composition (See Methods for further details).  
133  
134 To assess the relationship between  $\alpha$ -diversity of each group (fish, invertebrates and bacteria)  
135 and food-web structures with site location within the catchment, we ran linear mixed model  
136 analysis. Drainage area (km<sup>2</sup>) was log transformed to fit model assumptions. For each dependent  
137 variable, drainage area and season were the fixed effects, while site was the random effect. We  
138 determined the overall effect of both factors using analysis of variance and contrast testing of  
139 estimated marginal means to determine the influence of seasonal changes on all  $\alpha$ -diversity and  
140 food-web elements (see Methods for details). To examine the effect of river distance on  $\beta$ -  
141 diversity we constructed a matrix of pairwise distances for sites that were connected along the  
142 fluvial network and to examine the effect of river distance on  $\beta$ -diversity we performed a Mantel  
143 test (see Methods and Supplementary information).

144

#### 145 *Spatial and temporal biodiversity patterns*

146 In total we detected 374 genera across all organismal groups associated with freshwater,  
147 including 12 fish genera, 80 invertebrate genera and 282 bacteria genera. When combining all  
148 seasons,  $\alpha$ -diversity (genus richness) ranged between 8–96 genera with all taxonomic groups  
149 combined (Fig. 1). Over the different seasons, mean local  $\alpha$ -diversity was 70 (range 10–92) in  
150 spring, 48 (range 8–85) in summer, and 63 (range 19–96) in autumn (See Supporting Information  
151 Fig. S1 and Table S3). We used mixed models to assess the influence of drainage area and  
152 season on the local  $\alpha$ -diversity of each group (Fig. 3, for model output see Supporting  
153 Information Table S4–S6). Of the three taxonomic groups, only fish  $\alpha$ -diversity significantly



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154 increased with the size of the drainage area ( $p < 0.001$ , Fig. 3a and Supporting Information for  
155 model output Table S4– S6), while for bacteria and invertebrates there was no significant  
156 relationship ( $p = 0.670$  and  $p = 0.239$ , respectively, Fig. 3c and 3e). There was, however, a  
157 significant seasonal effect in  $\alpha$ -diversity on invertebrate and bacteria genera ( $p < 0.001$  for both  
158 groups, Fig. 3d and 3f, see Supporting Information Table S4–S6). The influence of seasons can  
159 be seen further in the contrast testing (Fig. 3b, d and f and Supporting Information Table S7 for  
160 full contrast testing results), which shows invertebrate  $\alpha$ -diversity in spring was significantly  
161 higher compared to summer and autumn ( $p < 0.001$ , Fig. 3d), and bacteria  $\alpha$ -diversity in summer  
162 was significantly lower compared to spring and autumn ( $p < 0.001$ , Fig. 3f). Fish  $\alpha$ -diversity  
163 however did not vary significantly between seasons, with the mean number of 2 (range 0–6) fish  
164 genera remaining constant (Fig. 3b).

165  
166 Regarding the  $\beta$ -diversity across the catchment, the Jaccard's dissimilarity significantly  
167 increased with the river distance among sites in all organismal groups across all seasons, apart  
168 from bacteria in spring and autumn (fish Mantel statistics: Spring 0.143,  $p < 0.01$ , Summer  
169 0.171,  $p = 0.001$ , Autumn 0.321,  $p = 0.001$ ; invertebrate Mantel statistics: Spring 0.095,  $p < 0.05$ ,  
170 Summer 0.169,  $p = 0.001$  and Autumn 0.114,  $p < 0.05$ ; bacteria Mantel statistics: Spring -0.058,  
171  $p = 0.834$ , Summer 0.179,  $p < 0.005$  and Autumn 0.069,  $p = 0.12$ , See Supplementary  
172 Information Table S8). Further partitioned analyses on taxon replacement and loss revealed  
173 contrasting patterns. Taxon replacement between sites increased over river distance for all  
174 groups in most seasons (significant or marginally significant, see Table S8), apart from fish in  
175 spring (Mantel statistics 0.07,  $p = 0.891$ ) invertebrates in spring (Mantel statistics 0.066,  $p =$   
176 0.051) and bacteria in spring and summer (Mantel statistics 0.016,  $p = 0.34$  and Mantel statistics

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177 0.07,  $p = 0.068$ , respectively). In contrast, taxon loss was only found to significantly increase  
178 over river distance for fish in spring and autumn (Mantel statistics 0.219,  $p = 0.001$  and 0.059,  $p$   
179 = 0.05, respectively) and bacteria in summer (Mantel statistics 0.089,  $p < 0.05$ ).

180

### 181 *Spatial and temporal changes in food-web structure and functional characteristics*

182 We examined commonly used food-web structural characteristics (link density, connectance,  
183 nestedness, omnivory, coherence, number of links, modularity, and robustness), as well as  
184 functional characteristics (functional diversity and redundancy). Functional characteristics were  
185 examined by using the designated functional feeding groups (e.g., shredders and omnivorous  
186 fish), based on specialised feeding behaviours (Fig. 2 & Supporting Information Fig. S2). Here  
187 we describe the results of link density, connectance, nestedness and omnivory as the most  
188 ecologically important food-web descriptors in our study, while the results from the remaining  
189 descriptors (coherence, number of links, modularity, and robustness) are presented in the  
190 Supplementary Information (See Fig. S3). Drainage area did not significantly influence any of  
191 the food-web structures looked at (Fig. S3 and S4). However, season had a significant influence  
192 on the change in food-web structures (Fig. 4 and S4), namely, link density ( $p < 0.001$ , Fig. 4a),  
193 connectance ( $p < 0.001$ , Fig. 4b), nestedness ( $p < 0.001$ , Fig. 4c), and omnivory ( $p < 0.001$ , Fig.  
194 4c and see Supporting Information Table S4 - S6 for full results), indicating that seasonal  
195 variation is of more importance in food-web dynamics than site location within the riverine  
196 network. To examine seasonal variation further, we carried out contrast testing, which showed a  
197 range of seasonal change in food-web dynamics. In particular, spring had significantly higher  
198 link density than summer and autumn ( $p < 0.001$  and  $p < 0.001$ , respectively, Fig. 4a); autumn  
199 had significantly lower connectance than spring and summer ( $p < 0.001$  and  $p < 0.001$ ,

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200 respectively, Fig. 4b), and the same is true for nestedness ( $p < 0.01$  and  $p < 0.01$ , respectively,  
201 Fig. 4c); finally, summer had significantly higher omnivory than autumn ( $p = 0.001$ , Fig 4d, see  
202 Supporting Information Table S7 for full contrast testing results).

203  
204 Functional diversity (defined as the change in function feeding groups used in this study)  
205 significantly decreased with drainage area and was also significantly different across seasons ( $p$   
206  $< 0.05$  Fig. 5a and  $p < 0.001$  Fig. 5b, respectively, see Supporting Information Table S4 - S6 for  
207 full results), whereas only season has a significant influence on the functional redundancy ( $p <$   
208  $0.001$ , Fig. 5d). To further examine the changes in seasonal influence we compared seasonal  
209 values for all functional characteristics. Functional diversity in spring was significantly higher  
210 than in summer and autumn ( $p = 0.001$  and  $p = 0.001$ , respectively, Fig. 5b), while functional  
211 redundancy in summer was significantly lower than in spring and autumn ( $p < 0.001$  and  $p <$   
212  $0.001$ , respectively, Fig. 5d and Supporting Information Table S7).

213

## 214 **Discussion**

215

216 Studies of biodiversity and food-web assemblages in riverine networks are often constrained to  
217 local scales or aggregated to a single time point, which in essence fails to capture the spatial  
218 processes and the temporal fluctuations that together play a key role in community dynamics  
219 present within a river network<sup>8</sup>. Our study is a first assessment utilising data derived from eDNA  
220 metabarcoding to detect patterns of biodiversity and food-web characteristics across three major  
221 taxonomic groups, namely fish, invertebrates and bacteria, in a whole river network at a spatial  
222 and temporally large scale. In our study we find contrasting patterns of biodiversity across these

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223 groups, which indicates different mechanisms may shape these organismal communities. By  
224 using a metaweb approach, we showed a strong signature of seasonality in food-web structures  
225 across the river network. We also showed that functional characteristics are influenced by both  
226 spatial and temporal changes. Overall, our study supports the need to include both spatial and  
227 temporal scales in order to understand changes in ecosystems, particularly as we see increased  
228 effects of contemporary global change.

229

230 Aquatic biodiversity is subject to fluvial influences within a dendritic network, whereby spatial  
231 patterns of  $\alpha$ -diversity and  $\beta$ -diversity are known for key groups, such as fish, invertebrates and  
232 microbes<sup>11–14,34</sup>. Our data is congruent with previous studies on fish diversity<sup>11,33</sup>, in that both  $\alpha$ -  
233 diversity significantly increased downstream, and  $\beta$ -diversity (community dissimilarity)  
234 significantly increased with river distance in all three seasons. However, patterns for  
235 invertebrates and bacteria differed from the predictions, and exhibited no significant influence of  
236 drainage size on  $\alpha$ -diversity but were influenced by seasonal change. For invertebrates, seasonal  
237 variation can be linked directly to the emergence of the non-aquatic adult life stage of several  
238 macroinvertebrate genera we detected (Diptera, Ephemeroptera, Plecoptera and Trichoptera),  
239 which takes place in the late spring and summer months<sup>27</sup>, and literally removes these organisms  
240 from the aquatic food-web as they become air-bound and often end up in terrestrial food-webs.  
241 For the spatial patterns, past studies often looked at spatial scales much larger or much smaller,  
242 and thus disparity may be due to a mismatch in scale looked at here. For example, Finn and  
243 colleagues<sup>13</sup> suggested headwaters harbour disproportionately high invertebrates compared to  
244 lower points in the catchment, but their studied focused on small (1–2) and mid (3–4) stream  
245 orders only, whereas the sites in our study ranged from small to much larger rivers (stream

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246 orders 1–7, <sup>35</sup>). Contrastingly, when looking at scales about 50-fold larger, Altermatt and  
247 colleagues<sup>14</sup> showed the number of key aquatic invertebrate taxa (Ephemeroptera, Plecoptera and  
248 Trichoptera) increased with catchment size, however they also found a combination of local  
249 factors (catchment areas, drainage area, elevation and network centrality) had the greatest  
250 influence on local invertebrate  $\alpha$ -diversity. Possibly, the scale at which we study invertebrate  $\alpha$ -  
251 diversity and contributing local factors falls between such small-scale vs large-scale perspective,  
252 but instead we detected regional patterns where  $\alpha$ -diversity remains relatively constant  
253 throughout the catchment. Similarly, drainage area did not have a significant effect on bacterial  
254  $\alpha$ -diversity, and  $\beta$ -diversity increased with river distance in summer only. We can therefore  
255 postulate that aquatic bacteria are able to persist as they disperse through the catchment;  
256 however, the number of bacteria genera (the  $\alpha$ -diversity) that do persist are subject to seasonal  
257 influences. Our findings expand on past studies, highlighting the influences of scale and  
258 temporal variation on different groups, which is of utmost importance when trying to conserve  
259 biodiversity and understand the differing drivers behind these patterns in a river network.

260

261 By resolving the fundamental trophic relationships among broad feeding groups, we established  
262 a trophic interaction metaweb for the three taxonomic groups examined in this study. The meta-  
263 web with genus co-occurrence data thus allowed our investigation of both spatial and temporal  
264 influences on the characteristics of local food webs. We found that the most significant factor  
265 driving freshwater riverine food-web characteristics was season. All food-web structural  
266 characteristics (apart from the number of links and robustness) were lowest in autumn, despite  
267 overall  $\alpha$ -diversity being lowest in summer. This indicates that the food-web structural variation  
268 we detected is not merely reflecting the genera richness dynamics over seasons, but the genera

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269 composition dynamics instead. In other words, the structures of the food webs are more  
270 influenced by those genera absent in autumn. Indeed, previous studies on freshwater food webs  
271 that have examined temporal changes have often found reduced productivity as the main driver  
272 behind a declined food-web structure in winter vs summer<sup>20,36</sup>. Thus, the decrease in structure we  
273 captured in this study could be the start of the productivity restriction seen in food webs over the  
274 winter months. The less-connected and less-nested food-web structure also implies weaker  
275 resource competition among consumers, which may be necessary for their coexistence in the  
276 food web<sup>37</sup>, especially when competition becomes more costly with lower resource productivity  
277 in autumn.

278

279 Moving from broad food-web patterns to examining functional feeding groups enables us to  
280 study fundamental changes within the community and possible effects at the ecosystem level<sup>17</sup>.  
281 Interestingly, and contrary to the biodiversity patterns and food-web dynamics, we see  
282 significant effects of both drainage area and season on the functional diversity, which we found  
283 to be higher in smaller drainage areas and in spring. The spatial part of such a pattern along the  
284 hierarchical river network is demonstrated in the River Continuum Concept, which shows  
285 increased diversity of invertebrate functional feeding groups at low stream orders<sup>38,39</sup>. Whereas  
286 both drainage area and season influences functional diversity, season is the only significant  
287 influence on functional redundancy, with fewer genera per functional feeding group observed in  
288 summer rather than in autumn. These results indicate that in summer the genera absent are across  
289 functional groups, whereas in autumn the genera absent include whole functional feeding groups  
290 leading to the constriction of local food webs. The inconsistent temporal patterns of food-web  
291 structure versus functional characteristics further imply that multiple feeding groups share

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292 similar trophic roles in the food web (Fig. S2), though they each adopt specialised feeding  
293 behaviour within the catchment and thus perform distinctive ecological functions (e.g.,  
294 shredders, collectors, filterers). In other words, the structure and function of a food web does not  
295 necessarily match and synchronise (*sensu stricto*<sup>22,40</sup>). These results are particularly encouraging,  
296 because the patterns of both food-web structure and functional diversity are known to be  
297 important for ecosystem health assessment and identifying potential vulnerability to  
298 perturbation<sup>17,26,41</sup>. Addressing the consistency of their patterns across spatial and temporal scales  
299 will likely lead to novel and comprehensive understanding of biodiversity and ecosystem  
300 function loss due to environmental change.

301  
302 In our study, the functional feeding groups were defined at the level of genus, while we expect  
303 investigations at finer resolutions will be promising for future work that can reveal not only more  
304 accurate patterns, but also the influences of sampling taxonomic resolution. Similarly, our  
305 selection of focal taxa may have influenced the food-web patterns we detected. For example,  
306 algae become an increasingly important resource when moving from allochthonous inputs in  
307 headwaters to larger streams with increased light levels further down the catchment<sup>38,39</sup>. With the  
308 selected three key taxonomic groups in riverine ecosystems, we present a broad and relevant  
309 view capturing trophic roles from basal resources (cyanobacteria) to top consumers (piscivorous  
310 fish), captured by three relatively broad metabarcoding markers. However, we also by default  
311 excluded some further groups, such as algae or terrestrial taxa, which could have been relevant  
312 as primary producers and as terrestrial-aquatic linkages, respectively. The choice of taxonomic  
313 groups looked at was both methodologically defined, as well as driven by the goal to have an

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314 overseeable and clearly aquatic-focused view on food webs. Thereby, it captures by default a  
315 subset from the real-world food web in which more species are involved.

316

317 By using the eDNA technique, we gain three notable advantages: its scalability for monitoring  
318 complex and large systems, its reusable nature, and its being a non-invasive method of collecting  
319 biodiversity information<sup>42,43</sup>. Our understanding of how the information we ascertain from eDNA  
320 sample collection has greatly improved in recent years due to studies on the hydrological  
321 influences<sup>44</sup> and a general understanding of the rate of eDNA persistence in lotic ecosystems<sup>45</sup>.  
322 However, the successful detection of taxa with eDNA is also linked to the ecology of individual  
323 species<sup>45</sup>, and some seasonal variation in the detection of several taxonomic groups is known<sup>46–</sup>  
324 <sup>49</sup>. Therefore, it is possible that some taxa that were not detected in the colder season (autumn) in  
325 this study were false-negative records. However, these non-detections are likely linked to low  
326 abundance or low metabolic rates, and thus these species are, while not physically absent, at least  
327 “relatively absent” in ecological terms.

328

329 In summary, our work showed we can construct comprehensible food webs at a large scale and  
330 over time by using eDNA sampling and combining multiple markers. Based on the biodiversity  
331 patterns we observed that spatial and temporal influences are different across groups.  
332 Furthermore, temporal influences were the significant driver of change for commonly used food  
333 web descriptors. Our approach is a first demonstration of the application of eDNA to a complex  
334 river network for the reconstruction of food web patterns and can be easily replicated in other  
335 systems worldwide. As biodiversity in freshwater systems face huge threats from anthropogenic  
336 pressures, including global climate change, establishing vital information on the changes in



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337 biodiversity and food web composition over spatio-temporal scales is essential for the detection  
338 of these stressors in order to protect and conserve river systems.

339

## 340 **Methods**

341

### 342 *Site selection and eDNA sample collection*

343 Environmental DNA samples were collected from the edge of the waterbody using single use  
344 disposable 50 ml syringes. At each site on each sampling event, a total of 1 L of water was  
345 filtered through two 0.22 µm sterivex filters (Merck Millipore, Merck KGaA, Darmstadt,  
346 Germany), sealed with luer caps and placed in individually labelled bags. Sampling was carried  
347 out over five consecutive days in May (spring), August (summer) and October (autumn) in 2018.  
348 During the summer sampling campaign, four sites were dry and could not be sampled (total  
349 samples across all seasons is n = 215). Negative field control samples were collected on each  
350 sampling day by filtering 500 ml of ddH<sub>2</sub>O through a sterivex filter in the same way as field  
351 samples were collected (n = 15). Negative field samples were processed alongside field samples.  
352 All samples were placed in labelled bags and cooled in a cool box until frozen at -20 °C on  
353 return to the laboratory.

354

### 355 *Extraction and library preparation*

356 DNA extraction and first round PCR set up was carried out in a specialist eDNA clean lab, with  
357 separate lab facilities for post PCR workflows. Samples were extracted using DNeasy  
358 PowerWater Sterivex Kit (Qiagen, Hilden, Germany) following the manufacturer's protocol.  
359 Prior to extraction, each sterivex was defrosted at room temperature and then wiped with 10%

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360 bleach, then 70% ethanol solution prior to extraction to remove any DNA from the outside of the  
361 filters. Extraction controls were carried out alongside sample extractions and consisted of blank  
362 sterivex filters (n = 5). Samples selected at random were analysed using a QuBit 3.0 fluorometer  
363 for double stranded DNA concentration, values measured between 0.317 - 27.5 ng/μl. All  
364 negative controls (field and extraction) were tested and recorded below detection limits.

365  
366 Samples were sequenced with the following markers: a 106 bp fragment of the mitochondrial  
367 12S marker (<sup>50</sup>, hereafter referred to as 12S) used to amplify vertebrate DNA, a 313 bp fragment  
368 of the mitochondrial cytochrome oxidase I marker (<sup>51</sup> and <sup>52</sup>, hereafter referred to as COI) used to  
369 amplify metazoan DNA and a 450 bp fragment of the V3-V4 region of the 16S marker  
370 (hereafter, 16S) used to amplify bacteria and archaea DNA (See Supporting Information Table  
371 S8 for primer sequences). Positive controls (n = 6 per library prep, see Supporting Information  
372 Table S9) and PCR negative controls (2 μl of ddH<sub>2</sub>O, n = 11 per library prep) were included in  
373 each library. Each library consisted of 252 samples in total (including positive and negative  
374 controls).

375  
376 Library preparation followed a two-step PCR process for both the 12S and COI markers, the 16S  
377 library was carried out using a three-step PCR<sup>53</sup> (See Supporting Information Methods for full  
378 details), all samples were amplified in triplicate. After the initial amplification, where Nextera®  
379 transposase sequences (Microsynth, AG, Balgach, Switzerland) are added to the PCR product, all  
380 samples were tested for amplification success with the AM320 method on the QiAxcel Screening  
381 Cartridge (Qiagen, Germany). PCR products were cleaned using ZR-96 Plate clean-up Kit  
382 (Zymo Research) following the manufacturers protocol with the minor modification by which

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383 the elution step was prolonged to 2 minutes at 4000 g. The clean amplicons were indexed using  
384 the Illumina Nextera XT Index Kit A, C and D following the manufacturer's protocol (Illumina,  
385 Inc., San Diego, CA, USA). A reaction contained 25  $\mu$ L 2x KAPA HIFI HotStart ReadyMix  
386 (Kapa Biosystems, Inc., USA), 5  $\mu$ L of each of the Nextera XT Index adaptors and 15  $\mu$ L of the  
387 DNA templates. The final PCR products were then cleaned using the Thermo MG Magjet bead  
388 clean up kit (Thermo Fisher Scientific Inc., MA, USA) and a customized programme for the  
389 KingFisher Flex Purification System (Thermo Fisher Scientific Inc., MA, USA) in order to  
390 remove excessive Nextera XT adaptors. The cleaned product of 50  $\mu$ l was then eluted into a new  
391 plate and stored at 4 °C prior to quantification. For each library, the clean indexed amplicons  
392 were quantified in duplicate on a Spark Multimode Microplate Reader (Tecan, US Inc. USA)  
393 prior to equimolar pooling using the BRAND Liquid Handling Station (BRAND GMBH + CO  
394 KG, Wertheim, GE). Negative extraction and PCR controls were added according to their  
395 concentration. Library concentration was quantified on the Agilent 4200 TapeStation (Agilent  
396 Technologies, Inc., USA) and verified by the Qubit the HS Assay Kit. Paired-end sequencing  
397 was performed on an Illumina MiSeq (Illumina, Inc. San Diego, CA, USA) at the Genetic  
398 Diversity Centre at ETH (See supporting information Table S1 for library loading information).  
399

#### 400 *Bioinformatics*

401 After each of the libraries were sequenced, the data was demultiplexed and reads were quality  
402 checked using usearch v11.0.667<sup>54</sup> and FastQC<sup>55</sup>. Raw reads were first end-trimmed, merged  
403 and full-length primer sites were removed using usearch v11.0.667<sup>54</sup> (16S reads were merged  
404 using Flash v1.2.11,<sup>56</sup>). The merged and primer trimmed reads were quality filtered using  
405 prinseq-lite (0.20.4). The UNOISE3 (usearch v11.0.667) workflow with an additional clustering

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406 of 99% (usearch v11.0.667) identity was applied to obtain error corrected and chimera-filtered  
407 sequence variants ZOTUs. The ZOTUs were then clustered using a 97 %, similarity approach  
408 and taxonomic assignment with a 0.85 confidence threshold was performed using SINTAX in  
409 the usearch software v11.0.667<sup>54</sup> with following databases: 12S: NCBI BLAST (v200416), COI:  
410 Custom reference database (Including MIDORI un-trimmed (V20180221) and 16S: GreenGenes  
411 (V13.5), RDP (160411) and SILVA (V128). See Supporting Information Methods for all  
412 bioinformatic parameters and reference database information used for each library. Prior to  
413 downstream analysis, 0.1% of reads were removed from each sample to reduce errors caused by  
414 tag-jumping or minor contamination in library preparation<sup>57</sup>.

415

416 *Biodiversity patterns*

417 We calculated  $\alpha$ -diversity (genus richness) at each site and compared  $\beta$ -diversity between sites  
418 by using Jaccard dissimilarity using the betapart R-package<sup>58</sup>. We constructed a matrix of  
419 pairwise distances between sites along the fluvial network with the igraph R-package<sup>59</sup> and  
420 compared the similarity between  $\beta$ -diversity and river distance using the Mantel test with the  
421 vegan R-package<sup>60</sup>. To further partition  $\beta$ -diversity into species loss and replacement, sites which  
422 did not record genus from a target group were removed from the analysis of that group only.

423

424 *Feeding group assignment*

425 Feeding groups were determined based on literature, species inventories and targeted expert  
426 knowledge<sup>61,62</sup> for fish and invertebrates. Genera of bacteria were included if the phyla they  
427 belong to has a strong association with freshwater habitat<sup>63</sup>, bacteria were then broadly divided  
428 into heterotrophic and cyanobacteria, the latter constituting a basal resource. A constant basal

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429 resource of detritus was also included in all food webs (See Supporting Information Table S2 for  
430 assignment of genera to feeding groups).

431

#### 432 *Food-web structure*

433 We constructed a metaweb based on known trophic relationships among feeding groups  
434 (Supplementary Table S2), then defined local food webs using this metaweb at each field site,  
435 based on co-occurrence of genera (nodes) and their interactions (links). The metaweb approach  
436 has been applied to identify food-web characteristic change across spatial gradients in terrestrial  
437 ecosystems<sup>32</sup>, and temporal changes in aquatic ecosystems<sup>24</sup>, but has yet to be used at a large  
438 spatial scale in an aquatic ecosystem over time.

439

440 We then quantified common food-web structural characteristics for each local food web  
441 generated. These included fundamental node-link composition features, i.e., number of links (L),  
442 link density (L/S, the number of feedings links per taxa divided by the genus  $\alpha$ -diversity at each  
443 site) and connectance (L/S<sup>2</sup>, the proportion of realised interactions). To further explore the  
444 holistic topology of these food webs and their change over space and time, we adopted the  
445 following indices to determine some more key features. Nestedness is an indication that the diets  
446 of specialist taxa are subsets of generalist taxa's diets, and was calculated using the nestedness  
447 metric based on Overlap and Decreasing Fill (NODF) function in vegan<sup>60</sup>. Modularity is  
448 indication of a less nested network<sup>64</sup> in that the nodes are characterised into modules which,  
449 unlike nested structures, do not overlap, and was calculated using the `multilevel.community()`  
450 function from the `igraph` package<sup>59</sup>. Omnivory is defined as the proportion of taxa with a mixed  
451 trophic level diet. Thus, the more omnivores a community has, the less coherent the food web<sup>65</sup>.

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452 Omnivory is often debated as a measure of food-web stability, and weak omnivorous interactions  
453 are likely to lead to a more stable food web<sup>66</sup>. Trophic level of genera and omnivory were  
454 calculated using the methods stated in William and Martinez<sup>21</sup>. Coherence is defined as the  
455 overall degree of homogeneity of the difference between trophic levels of every consumer-  
456 resource pair within the local food web. As described by <sup>65</sup>, the coherence of a network can  
457 reliably be used to establish the stability of a network by looking at the distribution of trophic  
458 distances over all links in each network. For example, a perfectly coherent network ( $q = 0$ )  
459 implies that each taxon within the food-web only occupies a single trophic level. Coherence was  
460 calculated using the methods stated in Johnson et al<sup>65</sup>. Robustness was defined by Dunne and  
461 Williams<sup>5</sup> as the “*proportion of species subjected to primary removals that resulted in a total*  
462 *loss ... of some specified proportion of the species*”. In our study we used 50% as the proportion  
463 of species lost and excluded basal resources for primary removal. Robustness was calculated  
464 using the methods stated in Dunne and Williams<sup>5</sup>.

465

466 To explore the change in functional characteristics within the food webs, we used the broad  
467 feeding groups as described when constructing the interaction network (See Fig. 1 and Fig. S2).  
468 Functional diversity was calculated as the number of feeding groups that had at least one genus  
469 present in the sample. Functional redundancy was calculated as  $\alpha$ -diversity divided by functional  
470 diversity, reflecting the average number of genera within a feeding group.

471

472 *Data analysis*

473 We ran linear mixed model analysis to assess the relationship between group genus  $\alpha$ -diversity  
474 (bacteria, invertebrates and fish), food-web structural characteristics (coherence, connectance,

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475 link density, number of links, omnivory, modularity, nestedness and robustness) and functional  
476 characteristics (functional diversity and redundancy) with site location within the catchment.  
477 Drainage area (km<sup>2</sup>) was log transformed to fit model assumptions. For each dependent variable,  
478 drainage area and season were the fixed effects. We included site as a random effect to account  
479 for repeated sampling of sites (e.g., genus  $\alpha$ -diversity  $\sim$  drainage area + season + (1 | Site)).  
480 Significance was calculated using the lmerTest R-package<sup>67</sup>, which applies Satterthwaite's  
481 method to estimate degrees of freedom and generate p-values for mixed models (Table S4 and  
482 S5). We then used anova() to see the overall effect of both factors: Drainage area and Season  
483 (Table S6) and follow up contrast testing were carried out using the emmeans R-package<sup>68</sup> to  
484 test for significant differences between seasons (Table S7).

485

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494

495 **Author contributions:**

496 R.C.B and F.A conceived the study. R.C.B performed the genomic lab analyses and J.C.W.  
497 performed the bioinformatics. R.C.B assigned trophic levels to all taxa and constructed the

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498 metaweb, and H.H performed food-web analysis. R.C.B performed all statistical analyses. R.C.B  
499 produced all figures and illustrations. All authors contributed to the interpretation of the  
500 networks and discussed and commented on the paper.

501

502 **Competing interests:**

503 The authors confirm there are no competing interests.

504

505 **Materials & Correspondence:**

506 Correspondence to Rosetta C. Blackman or Florian Altermatt

507

508 **Data availability**

509 Sequencing data generated during this study will be made available in a public repository upon  
510 publication.



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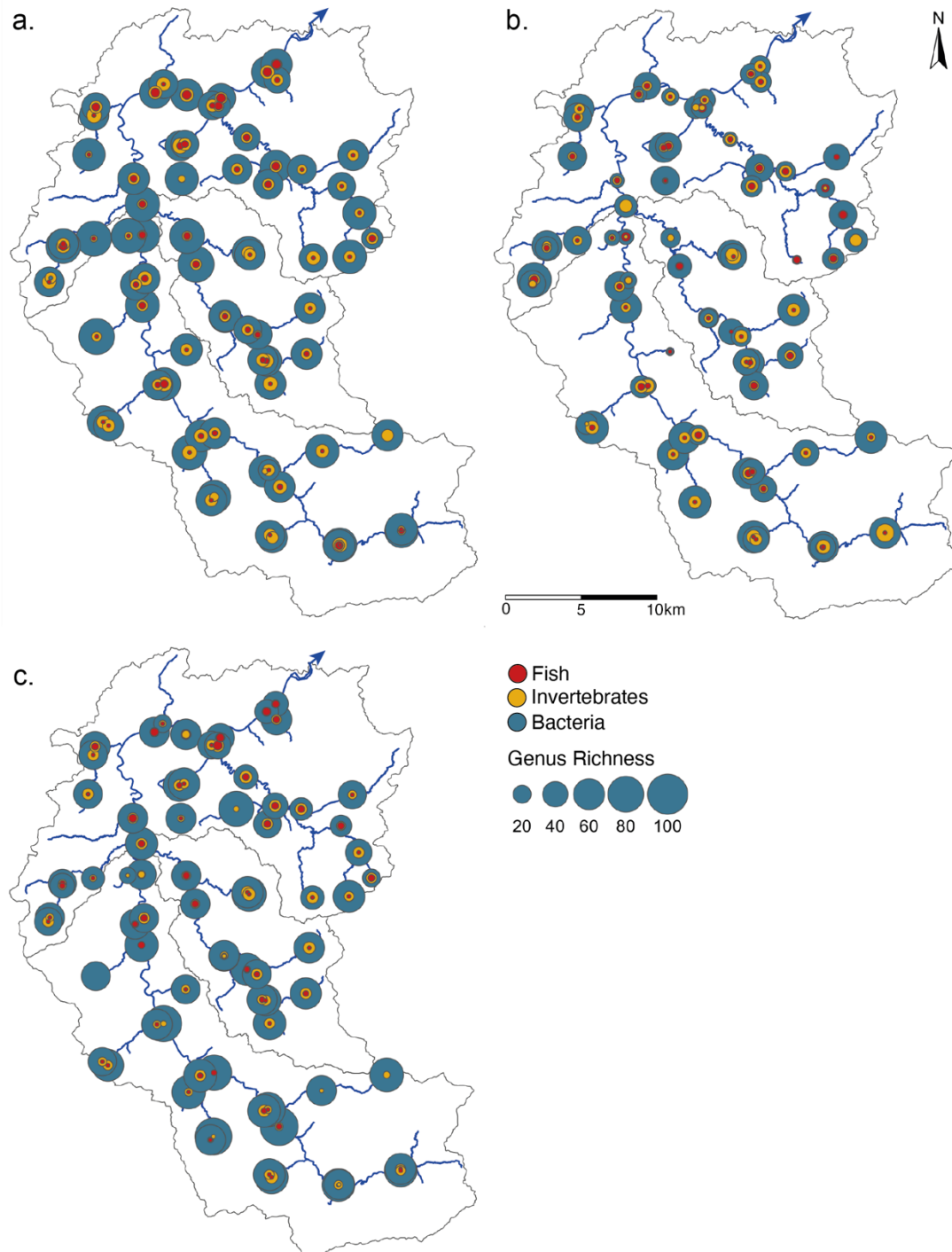
661 **Figures:**

662 **Figure 1: Genus  $\alpha$ -diversity of bacteria, invertebrates and fish collected from eDNA**

663 **samples in the Thur catchment in (a) spring, (b) summer and (c) autumn. The circles are**

664 **scaled proportionate to the  $\alpha$ -diversity of each group. Grey lines give the sub-catchments Glatt,**

665 **Necker, and Thur, respectively and the blue arrow shows the direction of flow.**



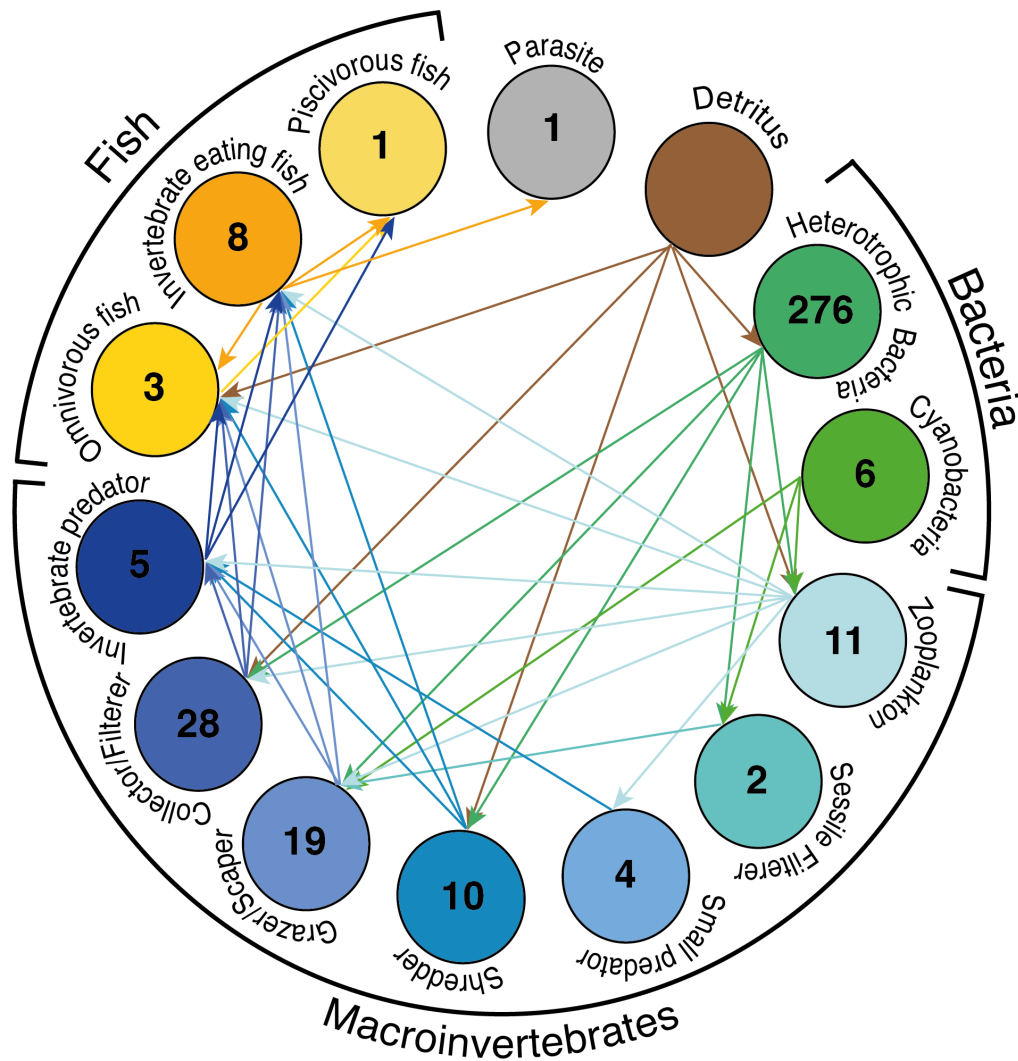
666

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668 **Figure 2: Food-web network generated from eDNA data.** All genera were categorised into  
669 feeding groups dependant on their dominant feeding behaviour, we then used this information to  
670 construct a trophic interaction metaweb using these links. Number of genera in each group is  
671 shown in circles, arrows indicate energy flow.

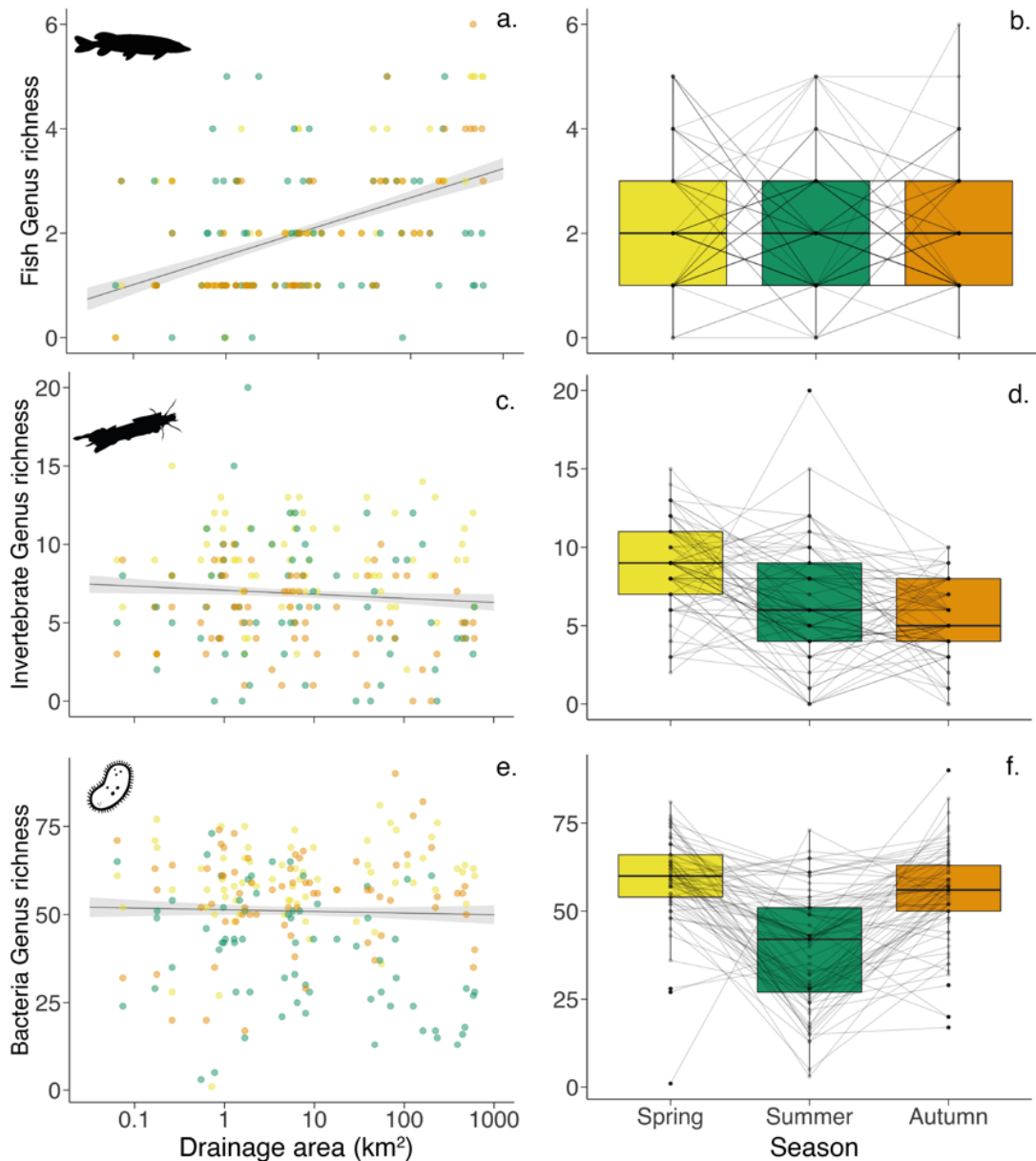


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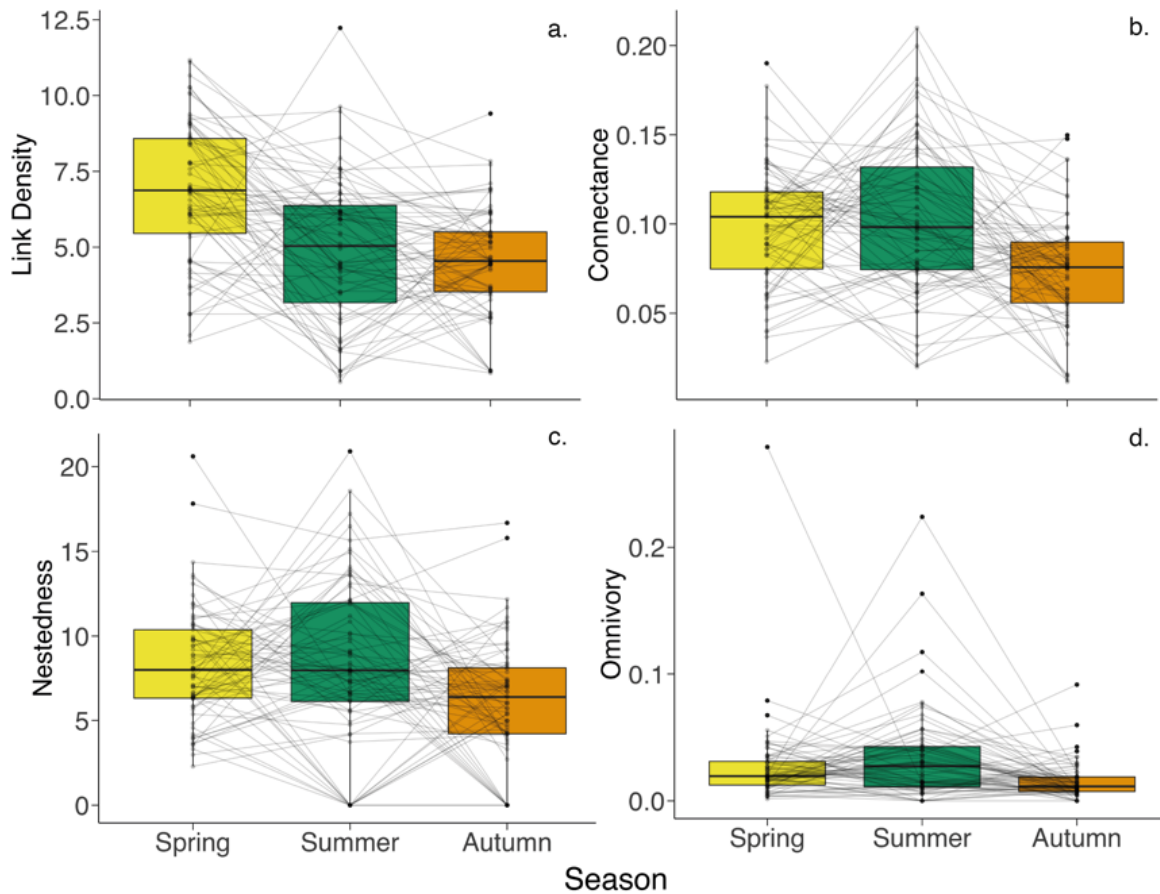
674 **Figure 3: Genus  $\alpha$ -diversity in space and time.** Plots a, c and e show  $\alpha$ -diversity in each group  
675 as a function of drainage area. Line indicates linear mixed model with shaded area showing 95%  
676 confidence intervals as calculated using the model predictions and standard error. Plots b, d and f  
677 show change in  $\alpha$ -diversity in each group over season. Grey lines indicate link sample points  
678 over the three sampling seasons. In all plots colour represents season: yellow – Spring, green –  
679 Summer and orange – Autumn.



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681 **Figure 4: Food-web structural characteristics:** Box plots showing the change in each food-  
682 web structural characteristic over the three seasons: a: Link Density, b: Connectance,  
683 Nestedness and d: Omnivory. Grey lines indicate link sample points over the three sampling  
684 seasons and colour represents season: yellow – Spring, green – Summer and orange – Autumn.

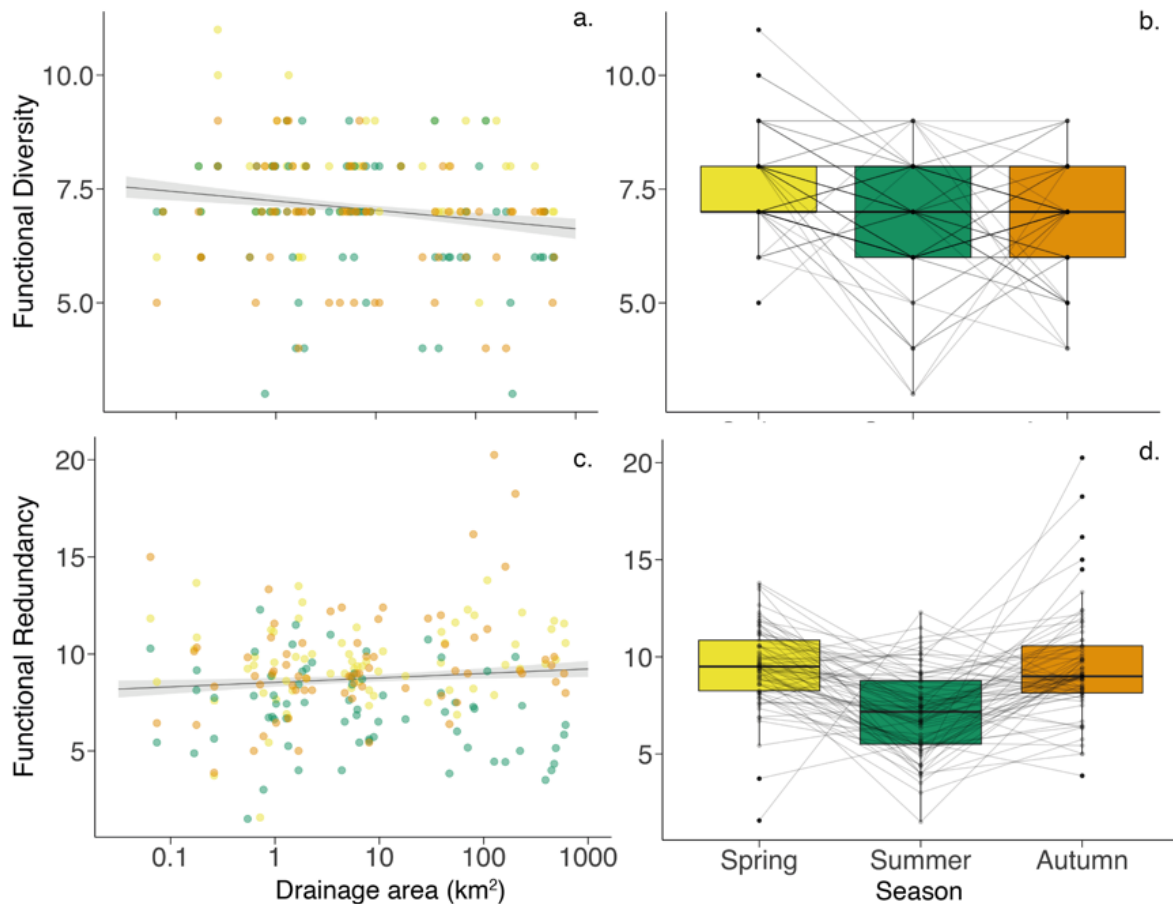


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687 **Figure 5: Functional diversity and functional redundancy.** a and b: Functional Diversity, c  
688 and d: Functional Redundancy. Plots a and c show the change over drainage area. Line indicates  
689 linear mixed model with shaded area showing 95% confidence intervals as calculated using the  
690 model predictions and standard error. Plots b and d show change over season. Grey lines indicate  
691 link sample points over the three sampling seasons and colour represents season: yellow –  
692 Spring, green – Summer and orange – Autumn.



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