

1 **Climate-warming alters the structure of farmland tri-trophic ecological networks and**
2 **reduces crop yield**

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18 **Running title:** Climate-warming alters ecological networks

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26 **Abstract.** It is unclear how sustained increases in temperature and changes in precipitation, as
27 a result of climate-change, will affect crops and their interactions with agricultural weeds,
28 insect pests and predators, due to the difficulties in quantifying changes in such complex
29 relationships. We simulated the combined effects of increasing temperature (by 1.4°C over a
30 growing season) and applying additional rainwater (10% extra per week) using a replicated,
31 randomized block experiment within a wheat crop. We examined how this affected the
32 structure of 24 quantitative replicate plant-aphid-parasitoid networks constructed using DNA-
33 based methods. Simulated climate-warming affected species richness, significantly altered
34 consumer-resource asymmetries and reduced network complexity. Increased temperature
35 induced an aphid outbreak but the parasitism rates of aphids by parasitoid wasps remained
36 unchanged. It also drove changes in the crop, altering in particular the phenology of the wheat
37 as well as its quality (*i.e.* fewer, lighter seeds). We discuss the importance of considering the
38 wider impacts of climate change on interacting-species across trophic levels in agro-
39 ecosystems.

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51 **Introduction**

52 Climate change is expected to have profound impacts on food production systems over the
53 coming decades (Lobell *et al.* 2008). Crops will be adversely affected by a combination of both
54 abiotic (e.g. heat, drought, salinity and submergence in water) and biotic (e.g. pests and
55 pathogens) stresses (Baulcombe *et al.* 2009; Maxmen 2013; Bebber *et al.* 2014; Lesk *et al.*
56 2016), posing significant threats to food security (Godfray *et al.* 2010). Despite the growing
57 research demonstrating the impacts of climate change on species abundances and distributions,
58 community composition and organismal physiology (Sala *et al.* 2000; Parmesan 2006; Garcia
59 *et al.* 2014), climate change effects on the networks of interactions among species are poorly
60 understood (Tylianakis *et al.*, 2008), particularly in agro-ecosystems. This is largely due to the
61 difficulties in quantifying changes in interactions compared with changes in biodiversity
62 (McCann 2007). Yet, complex networks of biotic interactions, such as insect pollination and
63 parasitism, play an important role in the maintenance of biodiversity (Bascompte *et al.* 2006),
64 provide valuable ecosystem services (Pocock *et al.*, 2012), and can mediate ecosystem
65 responses to environmental change (Sydes & Miller 1988; Brooker 2006). Species-interactions
66 may, however, be more susceptible to climate change, as they are sensitive to the phenology,
67 behaviour, physiology and relative abundances of multiple species (Memmott *et al.* 2007;
68 Suttle *et al.* 2007; Tylianakis *et al.* 2007).

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70 Combining advances in both network theory and molecular ecology offers unprecedented
71 opportunities to describe interactions between species, the structure of communities and the
72 function and stability of ecosystems (Evans *et al.* 2016). Ecological networks provide a
73 quantitative framework to unify the study of biodiversity and ecosystem function (Thompson
74 *et al.* 2012) and have been successfully used to quantify the ecosystem-level consequences of
75 global environmental change (Tylianakis *et al.* 2010). There is growing interest in developing

76 these approaches to provide a more holistic, systems-based understanding of agro-ecosystems
77 that could be used to maximise the ecosystem services provided by farmland biodiversity, as
78 well as for anticipating and mitigating future scenarios (Bohan *et al.* 2013). For example,
79 Macfadyen *et al.* (2009) constructed quantitative plant-herbivore-parasitoid networks on paired
80 organic and conventional farms and showed that the organic farms had more species across the
81 three trophic levels and significantly different network structure. However, such networks take
82 considerable effort to construct and can be subject to bias because of the limitations of
83 taxonomically selective rearing success as well as the reliance on accurate morphological
84 identification (Evans *et al.* 2016). Advances in DNA sequencing technologies provide
85 enormous potential to determine hitherto difficult to observe species interactions and thus to
86 produce highly-resolved ecological networks (Wirta *et al.* 2014; Derocles *et al.* 2018; Evans *et*
87 *al.* 2016). An accurate and cost-effective PCR diagnostics approach has recently been
88 developed to allow the rapid construction of quantitative ecological networks of farmland
89 aphid-parasitoid interactions (Derocles *et al.* 2012a, 2014) providing new opportunities to
90 examine the impacts of environmental change on network structure and complexity.

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92 In northern Europe, climate models predict significant warming and an increase in both
93 precipitation (mainly in winter) and the frequency of extreme weather events (IPCC 2014),
94 which are likely to cause significant damage to agro-ecosystems (Olesen *et al.* 2011). With
95 increasing evidence that present climate change is altering geographical ranges, population
96 dynamics and phenologies of some insects (Altermatt 2010; Morris *et al.* 2015), there is
97 growing concern that global food security is threatened by the emergence and spread of crop
98 pests and pathogens (Maxmen 2013). Given the ecological and economic importance of
99 phytophagous insects and their natural enemies, a greater understanding of their direct and
100 indirect interactions and how these respond to experimental manipulation is needed (van Veen

101 *et al.* 2006), particularly in the context of climate-warming.
102
103 Experimental manipulations of temperature and precipitation have provided important insights
104 into the responses of terrestrial ecosystems, with climate-warming generally stimulating total
105 net primary productivity, increasing ecosystem photosynthesis and respiration (see Wu *et al.*
106 2011 for a review). Real-world experimental climate manipulations can help to fill the
107 knowledge gap between highly controlled, closed-system laboratory studies (e.g. Le Lann *et al.*
108 2014) that tend to focus on a small number of species, and large scale open-field
109 experiments that rely on variations in temperature along environmental gradients (see de Sassi
110 & Tylianakis 2012; Romo & Tylianakis 2013). To date, most field-based simulated-warming
111 experiments have used infrared heating devices (see de Sassi *et al.* (2012) who used
112 underground heating cables) but have mainly focused on plant responses to elevated
113 temperatures. To our knowledge, none have examined the impacts on networks of interacting
114 species across multiple trophic levels. Within grasslands, de Sassi & Tylianakis (2012)
115 demonstrated that in a tri-trophic system of plants, herbivores and parasitoids, each trophic
116 level responded differently to warming and overall the community was increasingly dominated
117 by herbivores. Within arable crops, a small number of individual simulated climate-warming
118 studies have demonstrated a reduction in wheat yield (Fang *et al.* 2013) and increases in aphid
119 pests (Dong *et al.* 2013) and insect predators (Berthe *et al.* 2015). Thus it is unlikely that
120 climate-warming will affect species richness within arable crops, rather it will alter network
121 structure and complexity, in particular consumer-resource asymmetries (e.g. network
122 ‘generality’ - the mean effective number of lower trophic level species per higher trophic level
123 species) and interaction evenness, driven by changes in the abundances and frequency of
124 interactions between plants, aphids and parasitoids. However, predicting the specific impacts
125 on the complex pattern of interactions among species in a community remains a pressing

126 challenge (Staniczenko et al. 2017).

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128 Here, we experimentally increase temperature and rainwater within farmland plots consisting
129 of spring-sown wheat and common uncultivated plant (weed) species. The study is framed in
130 the context of understanding climate change implications as it relates to policy targets (e.g.,
131 limiting warming to 2°C) within North European agriculture (Olesen et al. 2011). We examine
132 the responses of quantitative plant-aphid-parasitoid networks, constructed using DNA-based
133 methods, as well as the impacts on crop yield. Although predicting the direct and indirect
134 responses of plants, phytophagous insects and their natural enemies to perturbation is a major
135 challenge, quantitative ecological networks are particularly well suited for assessing direct and
136 indirect interactions in the first instance (van Veen *et al.*, 2006). Our objectives are threefold.
137 (1) To construct replicated, quantitative tri-partite food-webs describing the interactions
138 between crop and non-crop plants, aphids and parasitoids. We apply a DNA-barcoding
139 approach to accurately and cost-effectively quantify the interactions of Aphidiinae
140 endoparasitoids with their aphid hosts. (2) To examine the combined effects of a 1.4°C
141 temperature elevation and increase in rainwater on measures of network structure and
142 complexity. We use suspended infrared heaters, which have been effectively applied in other
143 habitats for climate change simulation experiments (Price & Waser 2000; Wan *et al.* 2002;
144 Harte *et al.* 2015) to warm farmland plots *in situ*, and apply extra rainwater following
145 established protocols (Rollinson & Kaye 2012). We predict no impacts on total species
146 richness, but significant increases in aphid abundances in warmed plots due to a positive direct
147 effect on population growth rate (Barton & Ives 2014) and a corresponding increase in the
148 frequency of parasitoid interactions, potentially leading to changes in network consumer-
149 resource asymmetries and interaction evenness. As aphids and parasitoids are highly
150 specialized in agro-ecosystems (Le Ralec *et al.* 2011; Derocles *et al.* 2014), we do not expect

151 an increase in network connectance (a measure involving the number of interactions) in the
152 short-term, as this would indicate an expansion of generalism of the species involved. We test
153 this for both bipartite and tripartite networks. (3) To investigate the overall effects of warming
154 on crop yield and whether any changes can be mediated by an increase in rainwater (either as
155 precipitation or as added irrigation).

156

157 **MATERIALS AND METHODS**

158 *Experimental layout*

159 The study was conducted in 2013 at Stockbridge Technology Centre (STC), North Yorkshire,
160 UK (53°49' N -1°9' W), a conventional farm consisting of meadows and cereal crops used for
161 field experiments. The climate is temperate oceanic, with a mean minimum and maximum
162 annual temperature and precipitation of 5.5–14°C (8.6–19.1 °C during the experiment) and
163 537.7 mm (156.6 mm during the experiment) respectively. We established a replicated,
164 randomized block open-field experiment consisting of six replicates of four simulated climate
165 change treatments in a field of spring wheat (*Triticum aestivum* cultivar Tybalt) (see Berthe *et*
166 *al.* 2015, Figure S1, Supporting information). The four treatments consisted of: (W) 1.4°C
167 increase in temperature; (P) 10% increase in precipitation/rainwater per week, based on historic
168 records; (WP) warming and precipitation treatments combined; and (C) control (ambient
169 conditions). We refer to “climate-warming” when reporting the effect of warmed treatments
170 and “precipitation” when reporting the effect of additional rainwater treatments. Treatments
171 were randomly allocated to 2×2 m experimental plots that were each separated by 2 m of wheat
172 to provide a buffer and allow the free movement of insects. The W and WP treatments involved
173 suspending 240 V infrared heaters 1.5 m above each plot (following Rollinson & Kaye 2012),
174 consistently heating throughout the day and night: this primarily drives plant phenology rather
175 than heating the column of air (Kimball 2005; White *et al.* 2011). A ‘dummy’ heater of the

176 same size and shape was suspended in the non-heated plots to account for any possible effects
177 of shading/shelter.

178

179 A real-time proportional-integrative-derivative feedback system ensured constant temperature
180 plot warming through infrared radiometer (IRR) monitoring of surface temperatures in warmed
181 plots. Soil-surface temperatures were monitored by 6 Infrared Remote Temperature Sensors
182 (IR120; Campbell Scientific; Loughborough, UK), positioned 1.10 m above the plots and
183 directed to the middle of the plot and connected to a data logger (Campbell Scientific;
184 Loughborough, UK) to record the temperatures every 10s and to control the constant output of
185 the infrared heaters. Their positions were selected randomly, three within a heated plot (W,
186 WP) and three within an unheated plot (C, P). Our aim was for the system to increase the
187 temperature in the warmed plots by 2°C. Over the course of the experiment, temperatures were
188 raised, on average, by 2.2°C (standard deviation 0.6) in block 1; 1.1°C in block 2 (standard
189 deviation 0.6) and 1.1°C in block 3 (standard deviation 0.8) that most likely reflected subtle
190 microclimate differences within the field. This provided a mean temperature increase of 1.4°C
191 (standard deviation 0.9) across all the plots. Increased rainwater was simulated in the P and
192 WP plots by manually adding 10% extra collected rainwater each week based on STC mean
193 monthly rainfall data collected between 2002 and 2012. This can either be interpreted as
194 representing weather conditions in a warm and wet summer, or a farmer increasing irrigation
195 to mitigate the effects of a warm and drier summer. We added the following water each week:
196 13 L in April; 19 L in May; 24 L in June; 26 L in July and 30 L in August, amounting to 407
197 L in total for each plot. During the course of the experiment, just 156.6 mm of rainfall was
198 measured at Stockbridge Technology Centre, well below the annual average. Thus we actually
199 increased precipitation/rainwater by 65% that year. The experimental area in which the plots
200 were located received herbicide applications on 2nd April and 13th May (pendimethalin;

201 metsulfuron-methyl and thifensulfuron-methyl); our aim was to allow some weed growth
202 without out-competing the wheat. Experimental treatments commenced immediately after the
203 sowing of spring wheat on 13th April and stopped with the harvest of the crop on 16th August.

204

205 *Plant surveys and crop yield*

206 Plants were identified to the species level, with a small proportion to the genus or family, and
207 the percentage cover of each was recorded weekly (18 surveys) in each plot. The date of
208 emergence of the first leaf and the date of emergence of the first ear for *T. aestivum* was
209 recorded in each plot and converted into Julian date for statistical analysis. At harvest, a
210 0.5×0.5m quadrat was placed in the area directly below the heaters/dummy heaters (we selected
211 this area because the heating pattern is likely to be more consistent; Kimball 2005) and the
212 number of *T. aestivum* ears counted. The density of wheat (number of wheat ears m⁻²) was then
213 calculated for each plot. We also harvested five ears randomly from each plot, which were
214 dried in an oven at 80°C for 48 hours in the laboratory. The seeds were counted and the total
215 seed weight was measured for each ear. For each plot, crop yield (g/m²) was calculated as:
216 (total seed weight / ear) x density of wheat.

217

218 *Insect surveys*

219 Plant-aphid interactions were recorded by systematically searching each plot and counting the
220 total number of aphids and visibly parasitized aphids ('mummies') on each plant species every
221 week (18 surveys) throughout the sampling period. We collected up to 30 aphid individuals per
222 colony and placed them in a 1.5ml tube filled with 95% ethanol and then stored at -20 °C in
223 the laboratory for later identification (see below). All aphid mummies were collected and stored
224 in 1.5ml tubes, but without 95% ethanol. Instead, these were stored under laboratory conditions
225 and observed for 10 days for the emergence of adult parasitoids. Adult parasitoids and aphid

226 mummies where parasitoids did not emerge were then stored individually in a 1.5ml tube filled
227 with 95% ethanol at -20 °C.

228

229 *Insect identification*

230 Aphids were first identified morphologically following Blackman & Eastop (1994, 2000,
231 2006). We extracted the DNA of all the aphids collected using a hotshot DNA extraction
232 (Montero-Pau *et al.*, 2008). Aphid identification was confirmed with DNA barcoding: a
233 fragment 658 bp from Cytochrome C oxidase subunit I [COI] was amplified and sequenced
234 with the PCR conditions described by Derocles *et al.* (2012b) and the following primer pairs:
235 LCO1490 (5'-GGTCAACAAATCATAAAGATATTGG-3'; Folmer *et al.* 1994) and the
236 degenerate reverse primer HCO2198-puc (5'-TAAACTTCWGGRTGWCCAAARAATC-3';
237 Cruaud *et al.* 2010). Adult parasitoids and non-emerged parasitoids from the mummies (n =
238 181) were identified using the DNA barcoding tool described by Derocles *et al.* (2012b): a
239 fragment 658 bp from COI was amplified and sequenced to identify these parasitoids. Aphid-
240 parasitoid interactions and parasitism rates were determined using two different molecular
241 methods based on the extracted DNA of aphids. First, we used a multiplex PCR approach
242 developed by Traugott *et al.* (2008) on the aphid species collected on *T. aestivum* (*Sitobion*
243 *avenae* and *Metopolophium dirhodum*) to detect both primary and secondary parasitoids. We
244 used nine primary parasitoid and two hyperparasitoid species-specific primer pairs to detect
245 and identify immature primary and secondary parasitoids within cereal aphid hosts. Second,
246 for all the other aphid species, we used the approach developed by Derocles *et al.* (2012a) that
247 uses the sequences of a 210 bp fragment from the 16S gene to identify to species-level (in most
248 cases) the immature Aphidiinae parasitoids within an aphid host. To improve the reliability,
249 we added an 'in tube control' to determine if an absence of parasitoid detection is due to either
250 a true absence of parasitism or a technical problem during DNA extraction or PCR

251 amplification. For this, we followed the PCR protocol for parasitoid detection described by
252 Derocles *et al.* (2012a) and we added in the PCR-mix the aphid COI barcode assay described
253 above. A detection of a parasitoid within an aphid host is characterized by two bands on a 1.5%
254 agarose electrophoresis gel: a band of 658 bp (COI, aphid and parasitoid) and a band of 210 bp
255 (16S parasitoid); an unparasitized aphid is characterised only by the band of 658 bp, from the
256 aphid DNA. An absence of band indicates a failure from either the DNA extraction or the PCR
257 amplification. In this case, the PCR amplification is performed a second time. If after a second
258 PCR amplification a failure is observed, the individual is removed from the analysis. Sixteen
259 aphids were removed from the analysis following two PCR failures. We used two
260 hyperparasitoid species-specific primer pairs (Traugott *et al.* 2008) to detect the secondary
261 parasitoids in non-crop aphid species. We compared parasitism rate determined using this
262 method versus the conventional approach (i.e. the number of aphid mummies collected) /
263 (number of aphid counted).

264

265 *Insect abundance, species richness and parasitism rates*

266 For each plot, we pooled data across the sampling period to calculate:

- 267 1) percentage of aphids sampled: number of aphids sampled / number of aphids counted
- 268 2) aphid abundance: total number of aphids counted on each plant species throughout the
269 sampling period
- 270 3) total species richness
- 271 4) species richness per trophic level (i.e. plants, aphids, parasitoids)
- 272 5) parasitism rate using the DNA-based method: (the number of aphid mummies collected
273 + number of parasitised aphids detected) / (number of aphid mummies collected +
274 number of aphids collected);
- 275 6) parasitism rate using the conventional method (no DNA-based method): (the number

- 276 of aphid mummies collected) / (number of aphid counted);
- 277 7) multiparasitism rate using the DNA-based method: (number of aphids parasitised by at
278 least two detected primary parasitoid species / number of aphids collected + number of
279 mummies collected)
- 280 8) hyperparasitism rate using the DNA-based method: (number of aphids parasitised by a
281 secondary parasitoid + number of secondary parasitoids identified in mummies /
282 number of aphids collected + number of mummies collected).

283

284 *Ecological network construction, visualisation and description*

285 Plant-aphid-parasitoid quantitative networks were constructed for each plot by pooling data
286 collected during the course of the experiment. We visualised the tripartite interactions for each
287 of the four treatments (by pooling replicate data from replicate plot) using the “HiveR” package
288 (Krzywinski *et al.* 2011) in R 3.3.1 (R Core Team, 2016). We were particularly interested in
289 how the experimental treatments affects consumer-resource asymmetries, classically described
290 in network ecology as vulnerability and generality (i.e. the mean number of consumers per
291 prey, and the mean number of prey per consumer, respectively), as well as standard measures
292 of complexity (Bersier *et al.* 2002). They are well suited for describing antagonistic interactions
293 and the extent to which consumers are specialized to the resource and how the resource is
294 attacked by the higher trophic level (Wirta *et al.* 2014). For each of the 24 tripartite networks,
295 we calculated the following qualitative, unweighted quantitative and weighted quantitative
296 network descriptors described by Bersier *et al.* (2002) using ‘cheddar’ (Hudson *et al.* 2013)
297 and ‘bipartite’ packages in R 3.3.1 (Dormann *et al.* 2009): Link density (average number of
298 links per species: LD, LD’q, LDq); Connectance (proportion of possible links between species
299 that are realized: C, C’q, Cq); Vulnerability (mean effective number of higher trophic level
300 species per lower level species: V, V’q, Vq) and Generality (mean effective number of lower

301 trophic level species per higher trophic level species: G , $G'q$, Gq). We based our analysis on
302 weighted quantitative network descriptors (LDq , Cq , Vq and Gq) to specifically examine
303 changes in network complexity and consumer-resource asymmetries as they are commonly
304 used in ecological network studies and less prone to sampling biases (Tylianakis *et al.* 2007;
305 Macfadyen *et al.*, 2009; Wirta *et al.* 2014). As interaction evenness may be ecologically
306 important, and that these network descriptors are relatively insensitive to differences in the
307 evenness of the distribution of link magnitude, we calculated the quantitative tri-partite
308 interaction evenness (IEq) following Albrecht *et al.* (2007). To examine whether plant-
309 herbivore and herbivore-parasitoid interactions react differently to climate change, we also
310 calculated network descriptors for the plant-aphid and aphid-parasitoid bipartite networks
311 separately.

312

313 *Statistical analysis*

314 Statistical analysis was performed in R 3.3.1 (R Core Team, 2016). The effects of treatment on
315 the plants (including yield), insects, parasitism rates and network descriptor response variables
316 were examined using Generalized Linear Models (GLM) with a Gaussian family (except for
317 aphid abundance data, where a Poisson family was used). To account for the intercorrelation
318 between the network descriptors, and to reduce the probability of a type I error, we used a
319 Bonferroni-corrected α of 0.01 to assess the level of significance for the five network
320 descriptors (*i.e.* LDq , Cq , Vq , Gq and IEq , following Tylianakis *et al.* 2007). This correction
321 was used when assessing the effect of treatments on tri-partite network descriptors and on
322 bipartite (plant-aphid and aphid-parasitoid) network descriptors.

323

324 The effects of treatment on the crop phenology (Julian dates of emergences of first leaf and
325 first ear) were examined with Mann-Whitney tests. The effects of treatment on the crop (*i.e.*

326 number of seeds / ear, the seed weight / ear, the density of wheat and yield) were examined
327 using GLM with a Gaussian family. In addition to the climatic treatments, biological
328 interactions may also affect the crop yield (see Gagic *et al.* 2016). Non-crop plants are
329 competitors for space and resources with the crop (Fahad *et al.* 2015). *Sitobion avenae* and
330 *Metopolophium dirhodum* are aphid species feeding on the wheat which may alter the yield
331 (van Emden & Harrington 2007). In order to examine the potential impact of uncultivated
332 plants on the density of the wheat, a second GLM was performed with the percent cover of
333 non-crop plants included as a covariate. Similarly, when analysing the yield data, we included
334 the abundance of wheat aphids *S. avenae* and *M. dirhodum* as a covariate in a separate model
335 and compared the model fit with and without the covariates using Akaike Information Criteria
336 (AIC). In summary, we compared the AIC of the following models:

- 337 a) the effect of precipitation and increased temperatures on the density of the wheat versus
338 the effect of precipitation, increased temperatures and percent cover of non-crop plants
339 on the density of the wheat;
- 340 b) the effect of precipitation and increased temperatures on the crop yield versus the effect
341 of precipitation, increased temperatures and the abundance of wheat aphids on the crop
342 yield.

343 In addition, ANOVA was performed on these two model comparisons to test whether the
344 inclusion of covariates provided a significantly better fit to the model.

345

346 **Results**

347 We quantified 2836 interactions between eight plant species (6 plants identified to species
348 level, 1 to the genus level and 1 to the family level), 1946 aphids (1765 living aphids and 181
349 aphid mummies) belonging to six species, 761 primary parasitoids from 13 species and 129
350 secondary parasitoids from two species. Of the 129 secondary parasitoids identified, only 41

351 primary parasitoid – secondary parasitoid interactions were recovered. Consequently, primary
352 and secondary parasitoids were considered as belonging to the same trophic level and separate
353 primary parasitoid – secondary parasitoid interactions were not examined (Figure 1). Overall,
354 the 1946 aphids included in the ecological network analysis represented 56.3% of the total
355 aphids counted in the experimental plots.

356

357 *Plant cover and richness*

358 We found no effect of treatment on plant species richness (GLM, warming: $F = 1.577$, $df = 1$,
359 $p = 0.223$; precipitation: $F = 3.09$, $df = 1$, $p = 0.093$; Table 1), but climate-warming significantly
360 reduced crop percentage cover (GLM, warming: $F = 11.746$, $df = 1$, $p = 0.003$; precipitation: F
361 $= 1.043$, $df = 1$, $p = 0.319$). The overall non-crop species cover was significantly increased in
362 the warmed plots (GLM, warming: $F = 4.78$, $df = 1$, $p = 0.04$; precipitation: $F = 1.519$, $df = 1$,
363 $p = 0.231$).

364

365 *Aphid abundance and parasitism rates*

366 We found no effect of treatment on aphid species richness, but climate-warming resulted in
367 significant aphid outbreaks (GLM, $df = 1$, $p < 0.001$; Table 1), with four times as many aphids
368 in the warmed plots compared to control plots. The abundance of the wheat aphids *S. avenae*
369 and *M. dirhodum* doubled as a result of warming (GLM, $df = 1$, $p = 0.009$; Figure 1, Table 1).
370 Molecular analyses revealed high rates of parasitism (based on parasitoid detection within
371 aphids and mummies sampled; mean $36 \pm 1.7\%$) compared to the conventional ‘mummy’
372 collection/rearing method (based solely only on mummies sampled; mean $9.9 \pm 1.8\%$).
373 Climate-warming did not significantly change parasitoid species richness, although we did
374 detect a trend (GLM, $df = 1$, $F = 4.247$, $p = 0.052$). There were no significant effects of
375 treatment on parasitism rates nor multiparasitism (two primary parasitoids within a single

376 aphid) and hyperparasitism rates (aphids parasitised by secondary parasitoids), which were
377 relatively low across the treatments ($3.77 \pm 0.01\%$ and $7.38 \pm 0.01\%$ respectively; Table 1).

378

379 *Tripartite ecological network structure*

380 We found a significant effect of climate-warming on total species richness across trophic levels
381 (Table 1, Figure 1). Precipitation did not affect quantitative tripartite network descriptors V_q
382 (GLM, $F = 0.003$, $df = 1$, $p = 0.959$), IE_q (GLM, $F = 0.274$, $df = 1$, $p = 0.606$; Figure 2), LD_q ,
383 C_q and G_q (Table 2). Simulated climate-warming did not affect qualitative network descriptors
384 (Table S1), however it did significantly decrease quantitative tripartite V_q (GLM, $F = 10.063$,
385 $df = 1$, $p = 0.005$; Figure 2) and LD_q , but did not affect C_q , G_q (Table 2) and IE_q (GLM, $F =$
386 0.362 , $df = 1$, $p = 0.554$; Figure 2). Within the 24 networks, both aphids and parasitoids never
387 consumed more than three different species from the lower trophic level (Figure 1).

388

389 *Plant-aphid bipartite network structure*

390 Precipitation did not affect plant-aphid quantitative network descriptors V_q (GLM, $F = 0.425$,
391 $df = 1$, $p = 0.522$), IE_q (GLM, $F = 0.0001$, $df = 1$, $p = 0.991$; Figure 2), LD_q , C_q and G_q (Table
392 2). Likewise, climate-warming did not affect plant-aphid quantitative network descriptors V_q
393 (GLM, $F = 0.753$, $df = 1$, $p = 0.395$), IE_q (GLM, $F = 5.574$, $df = 1$, $p < 0.029$; Figure 2), LD_q ,
394 C_q and G_q (Table 2)

395

396 *Aphid-parasitoid ecological network structure*

397 Precipitation did not affect aphid-parasitoid quantitative network descriptors V_q (GLM, $F =$
398 0.005 , $df = 1$, $p = 0.944$), IE_q (GLM, $F = 1.091$, $df = 1$, $p = 0.308$; Figure 2), LD_q , C_q and G_q
399 (Table 2). However, climate-warming significantly decreased aphid-parasitoid quantitative
400 network descriptors V_q (GLM, $F = 18.456$, $df = 1$, $p < 0.001$) and LD_q , but did not affect C_q

401 and Gq. Climate-warming negatively affected aphid-parasitoid IEq (GLM, $F = 37.599$, $df = 1$,
402 $p < 0.0001$). This suggests that higher trophic interactions are more sensitive in our system and
403 was likely caused by an increase in the frequency of interactions between wheat aphids and
404 two primary parasitoid species: *Aphidius rhopalosiphi* and *Aphidius ervi*.

405

406 *Wheat phenology*

407 First leaves emerged three days earlier in the warmed plots (Mann-Whitney, $W = 118$, $p =$
408 0.002). First ears emerged eleven days earlier on average in the warmed plots (Mann-Whitney
409 $W = 144$, $p < 0.001$). Precipitation affected neither the emergence of the first leaves (Mann-
410 Whitney, $W = 63.5$, $p = 0.586$) nor the first ears (Mann-Whitney, $W = 72$, $p = 1$).

411

412 *Crop yield*

413 Climate-warming significantly reduced the seed number (GLM, $F = 4.272$, $df = 1$, $p = 0.041$,
414 Table 3), the seed weight (GLM, $F = 3.049$, $df = 1$, $p = 0.012$; Table 3) but not the density of
415 the wheat (GLM, $F = 2.109$, $df = 1$; $p = 0.161$; Table 3), resulting in no overall reduction in crop
416 yield (GLM, $F = 3.835$, $df = 1$, $p = 0.064$; Table 3). However, when including the detrimental
417 effect of non-crop plants or wheat aphid abundance in the models, we found a significant
418 decrease in wheat density (GLM, $F = 11.606$, $df = 1$, $p = 0.003$; Table 4) and crop yield (GLM,
419 $F = 6.33$, $p = 0.021$, $df = 1$; Figure 3; Table 4). Yield loss was not compensated by increased
420 rainfall (GLM, $F = 0.066$, $df = 1$; $p = 0.8$; Table 4). These models, which including wheat aphid
421 abundances and non-crop cover, provided a significantly better fit to the data than the models
422 considering experimental treatment alone (ANOVA; wheat density: $F = 95.582$, $p < 0.001$;
423 crop yield: $F = 14.663$, $df = 1$, $p = 0.001$) Table 5).

424

425

426 **Discussion**

427 We provide the first experimental evidence, to our knowledge, of the impacts of climate-
428 warming on the structure of tripartite ecological networks, constructed using a DNA-barcoding
429 approach. Experimental warming altered total species richness across trophic levels (but not
430 plant and aphid species richness respectively), it significantly reduced crop percentage cover
431 and substantially increased aphid abundance (the abundance of the economically important
432 aphids *S. avenae* and *M. dirhodum* doubled as a result of warming). This affected quantitative
433 network structure and complexity, including aphid-parasitoid interaction evenness. Molecular
434 analyses revealed much higher rates of parasitism compared to traditional rearing/identification
435 methods, with generally fewer natural predator species in the warmed plots. However there
436 were no significant effects of treatment on parasitism rates, nor multiparasitism and
437 hyperparasitism. Thus, in the short-term at least, natural pest control (assessed here using a
438 molecular approach to determine parasitism rate) provided by parasitoids appears unaffected,
439 although studies of aphid and parasitoid population dynamics over the long-term are needed.
440 Overall, we show that wheat grown 1.4°C above ambient temperature produced significantly
441 fewer and lighter seeds resulting in a reduction in crop yield, with the best fitting model
442 including aphid abundance and non-crop cover as covariates. We found no statistically
443 significant effect of increased rainwater on any of our response variables, despite it being a
444 very low rainfall season.

445

446 *Study limitations*

447 Despite the advances made by our study, there are important limitations to our experiment.
448 First, the 4 m² plots sampled are not directly comparable to a large cereal crop field. Our results
449 may instead reflect how agricultural communities at field edges respond to climate change.
450 However, because insect herbivory and parasitism rate are edge-dependent (Maron & Crone

2006; Reeve & Cronin 2010), our results might nevertheless be indicative of the direction of change for plant and animal populations and communities at larger spatial scales as a result of climate-warming, although more research is necessary. Although all simulated climate-warming methods have limitations (Sassi *et al.* 2012), they are nevertheless one of the few tools available in empirically testing how ecosystems response to climate change and provide much-needed data for predictive network models (Staniczenko *et al.* 2017). In the future, complementary approaches including large-scale field experiments and small-scale mesocosms or laboratory experiments (see Romo & Tylianakis 2013) might give a more comprehensive view of the ecosystem response to climate change. Second, we did not control non-crop plant or insect communities as we wished to quantify how they interact. Thus, conventionally managed cereal crops are likely to have responded differently to the experimental treatments. Third, we only examined the effects of treatment over a single growing season. Further temporal replicates would determine whether the response observed is year-dependent and the extent of interaction turnover (Kemp *et al.* 2017). Fourth, we did not consider other organisms potentially affecting the plant-aphid-parasitoid networks, such as ants interacting with aphids or predators consuming both aphids and parasitoids (Traugott *et al.* 2011; Barton & Ives 2014; Raso *et al.* 2014). Future studies should examine a more exhaustive range of species interactions (e.g. following Pocock *et al.* 2012; Evans *et al.* 2013), which are increasingly possible using the molecular approaches described here and/or Next Generation Sequencing technologies (Kitson *et al.* 2018). Fifth, we could not disentangle whether the insect responses were mainly due to foraging decisions of organisms (*i.e.* dispersal between the plots) or their demographic response to climatic manipulation (*i.e.* treatments affecting population growth rates), although it is likely that the observed aphid species responses were demographic. Further experimental manipulations at larger-spatial scales (and including other important factors such as elevated CO₂) are urgently required as well as more detailed observations of host-parasitoid

476 and other predator-prey interactions, although this would need to involve much larger
477 controlled enclosures than are currently available. Finally, we conducted a relatively
478 exhausting sampling where all aphid mummies and more than 50% of aphids were collected
479 for further molecular analyses. Such intensive sampling may certainly affect the aphid and
480 parasitoid population dynamics at the plot-level and could have potentially affected our results.
481 However, adequate network analysis is very dependent on sampling completeness (Blüthgen
482 et al. 2006; Rivera-Hutinel et al. 2012; Jordano 2016). Consequently, such intensive sampling
483 is well established in studying host-parasitoid interactions (see Traugott et al. 2008) and
484 ecological networks more generally (e.g. Macfadyen *et al.* 2009) and was therefore necessary
485 for the purposes of this study. Assessing the effect of climate change on aphid and parasitoid
486 dynamics, while also a major issue, would then require a different experimental design.

487

488 *Trophic level to network level responses*

489 When considering each trophic level separately, climate-warming promoted weed growth
490 (especially *Chenopodium album* and *Cirsium arvense*), which increased competition with the
491 crop and contributed to a reduction in crop percentage cover. At the second trophic level, there
492 was a fourfold increase in aphid abundance in the warmed plots, as we predicted, mostly driven
493 by aphids associated with *T. aestivum*. At the third trophic level, contrary to our predictions,
494 parasitism rates remained unchanged. However, a decrease in aphid-parasitoid interaction
495 evenness in the warmed plots suggests that climate-warming might benefit some parasitoid
496 species at the expense of others. Whilst both the reduction in crop yield and the aphid pest
497 outbreak followed the general patterns observed in other recent studies (Maxmen 2013; Dong
498 *et al.*,2013; Bebber *et al.* 2014; Liu *et al.* 2016), the significant effects on network structure
499 observed in this study provides new insights into how climate-warming affects entire
500 communities of interacting species. First, we found evidence that climate-warming affects tri-

501 partite consumer-prey asymmetries, with significantly lower network vulnerability and linkage
502 density. Second, connectance was not affected, most likely due to the high trophic
503 specialization for both aphids and associated parasitoid wasps (Le Ralec *et al.* 2011; Derocles
504 *et al.* 2014). Third, although there was no effect of treatment on tripartite interaction evenness,
505 climate-warming negatively affected bipartite aphid-parasitoid interaction evenness,
506 suggesting that higher trophic interactions might be more sensitive in our system. Indeed,
507 changes in tri-partite network structure are essentially driven by aphid-parasitoid interactions:
508 plant-aphid networks were not affected by simulated-warming while aphid-parasitoid linkage
509 density and vulnerability decreased. Overall, our results support the findings from de Sassi *et*
510 *al.* (2012) showing that climate-warming may have bottom-up effects (on host density and
511 body size) which can in turn affect the structure of host-parasitoid networks.

512

513 *Parasitism*

514 We found no effect of climate-warming on the parasitism rate and species richness of parasitoid
515 wasps (although precipitation and warming treatment tended to decrease parasitoid richness)
516 which are intimately linked to the ecosystem service of natural pest control (Traugott *et al.*
517 2008; Derocles *et al.* 2014). In Northern European agricultural habitats, the most abundant
518 parasitoid species appear more specialized, with reduced attack rates on alternative hosts
519 (Derocles *et al.* 2014). Macfadyen *et al.* (2009) showed significant differences in network
520 structure between organic and conventional farms with more species at three trophic levels
521 (plant, herbivore and parasitoid) on organic farms. Despite herbivores on organic farms being
522 attacked by more parasitoid species, differences in network structure did not affect parasitism
523 rate across a variety of host species. In our study, climate-warming mainly influenced two
524 parasitoid species, *A. rhopalosiphi* (the main natural enemy of *Sitobion avenae*) and *A. ervi*,
525 driving a decrease in aphid-parasitoid interaction evenness. These species differ in their trophic

526 specialization: *A. rhopalosiphi* is a specialist and *A. ervi* is a generalist (Kavallieratos *et al.*
527 2004; Starý 2006). Previous work by Le Lann *et al.* (2014) under laboratory conditions showed
528 a decrease in the attack rate of *A. rhopalosiphi* on *S. avenae* as a result of warming, whereas
529 aphid defense rate increased. Under more realistic field-based scenarios, which include a
530 greater range of interacting species, we found the opposite effect. This not only suggests that
531 the degree of specialization may not necessarily explain which species will be more adaptable
532 to environmental changes (as hypothesized by Rand & Tschardt 2007; Tylianakis *et al.* 2008;
533 Jeffs & Lewis 2013) but that other factors, such as changes in apparent competition (Morris *et*
534 *al.* 2004), might be important considerations within a food-web context. Overall, an accurate
535 assessment of natural pest control cannot be undertaken by the single measure of parasitism
536 rate, but would require a careful examination of host and parasitoid population dynamics
537 through further study and a different experimental design. These results, together with a recent
538 study by Berthe *et al.* (2015) at the same study site that showed significant increases in
539 Coleoptera activity-densities but a reduction in community diversity as a result of climate-
540 warming, demonstrate the short-term impact of climate-warming on higher trophic levels (*i.e.*
541 predators and parasitoids) in particular. Given the potential top-down effects driven by these
542 organisms, we expect that climate-warming will result in long-term changes to the structure of
543 the ecological network and consequently in natural pest control. Thus long-term climate-
544 manipulation studies across spatial-scales are necessary to better understand the effects of
545 environmental change on agricultural plant-aphid-parasitoid interactions and the ecosystem
546 service of natural pest control (Cardinale *et al.* 2003; Tylianakis *et al.* 2006; Macfadyen *et al.*
547 2011; Peralta *et al.* 2014).

548

549 *Impacts of climate-warming on crop yields within an ecological network context*

550 We found significant effects of climate-warming not only on ecological network structure, but

551 also on crop yield. Experimental-warming has been shown to advance flowering and fruiting
552 phenology for a range of plant species (Sherry *et al.* 2007; Hovenden *et al.* 2008; Dong *et al.*
553 2013) and in our study, first wheat leaves emerged three days earlier on average and ears
554 emerged at least a week earlier in the warmed plots. Wheat grown under experimental-warming
555 produced fewer and lighter grain, resulting in a significant impact on crop yield. There was no
556 significant effect of increased rainwater, which was perhaps surprising given the study was
557 conducted during a very low rainfall season. The yield data from the experiment is nevertheless
558 not directly comparable with commercial agricultural wheat yields. It should be emphasized
559 that it was not our intention to simulate conventional farming methods, where routine spraying
560 would have removed most of the weed species within our plots. Rather we wished to study the
561 community wide response of interacting species across trophic levels. In this context, the
562 reduction in crop yield was primarily driven by a combination of the wheat producing fewer,
563 smaller grain as well as increased competition with weed species, rather than significant insect
564 damage (aphid load was very low: 0.14 ± 0.09 aphids per wheat ear across all plots). Despite
565 this, warming did trigger a fourfold increase in aphid abundance and this is likely to cause
566 significant damage to crops in years when fluctuating aphid numbers are higher. As
567 demonstrated recently by Gagic *et al.* (2016), attacks by several pests can have both positive
568 and negative impacts on crop yield. In our study, crop yield models produced a better fit when
569 pest aphid abundance was included as a co-variate. However, it still remains unclear how crop
570 (yield in particular) and non-crop plants are affected both directly and indirectly by changes in
571 aphid-parasitoid interactions. By pioneering new molecular methods to construct highly-
572 resolved species-interaction networks, we have provided new, cost-effective tools to examine
573 the response of communities of interacting agricultural species to environmental change.

574

575 *Merging DNA-based methods with ecological network analysis*

576 Merging molecular methods and ecological network analysis (ENA) provides new tools for
577 understanding ecology and evolution (Raimundo *et al.* 2018). Here we showed that the
578 detection-rate of aphid parasitism was more than three times higher using molecular assays
579 than by conventional insect-rearing approaches. Plant-aphid-parasitoid networks, constructed
580 using molecular methods, were more highly-resolved than traditional rearing methods, with
581 significant implications for host-parasitoid network-level analyses (Condon *et al.* 2014; Hrček
582 & Godfray 2015). Traditional approaches based on insect rearing and morphological
583 identification would have failed to detect changes in species interactions mediated by the
584 increase in temperature. Indeed, such approaches rely on the collection of aphid mummies and
585 rearing adults for identification. In our study, only 181 aphid mummies were collected while
586 709 parasitoids were detected and identified within their living aphid hosts. Parasitism cases
587 using molecular methods were therefore able to capture a more exhaustively range of host-
588 parasitoid interactions. These parasitism cases however still need to be considered cautiously:
589 parasitoid eggs or larvae detected do not always achieve their development to the adult stage
590 (Starý *et al.* 1989). Consequently, molecular tools could potentially overestimate parasitism
591 (Traugott *et al.* 2008). Moreover, aphids collected on the same plant were placed together in a
592 single tube. This may lead to a potential risk of contamination between aphids with parasitoid
593 DNA. But this risk is low because in the same tubes we found both unparasitised and parasitised
594 aphids (from different parasitoid species). Completely eliminating this risk would require each
595 collected aphid to be separately stored but might also result in unrealistic, time-consuming
596 sampling protocols.

597

598 In summary, this study provides the first evidence, to our knowledge, of the impact of climate
599 change on farmland tri-partite ecological networks, ecosystem services and agricultural output.
600 In the short-term, we highlight the potential winners (*i.e.* pests) and losers (*i.e.* pest natural

601 enemies) of agro-ecosystems in a warmer world. Overall, our study provides insights into the
602 potential threat of global warming on both farmland biodiversity and food production. Despite
603 limited changes to biodiversity *per se*, climate-warming affects the frequency of interactions
604 between species, ultimately affecting network structure, although the long-term consequences
605 of altered network structure on ecosystem functioning warrants further study. The detrimental
606 impact of climate-warming on wheat suggests the need for adapting future agricultural methods
607 of cropping in response to a climate change (Asseng *et al.*, 2013); cropping methods which in
608 turn can also have cascading effects on agro-ecosystems and their networks of interactions.
609 Considering the effects of environmental changes on ecological networks in dynamic models
610 rather than snapshots of communities is essential (Säterberg *et al.* 2013) as well as taking into
611 account a more complete range of interactions (*i.e.* ‘networks of ecological networks’; Pocock
612 *et al.* 2012; Evans *et al.* 2013). Future studies should consider the combined effects of climate-
613 warming and elevated CO₂ as the latter also affects wheat growth and grain yield in particular
614 (O’Leary *et al.* 2015). Such changes in plants may also induce bottom-up effects on high
615 trophic levels (*e.g.* pest arthropods feeding on the crop). Finally, increased rainwater did not
616 affect the ecological networks and the crop yield in the present study, suggesting that extra
617 water (either as increased precipitation or irrigation) might not mitigate the effects of increased
618 temperature. Further considerations are nevertheless needed to understand the predicted
619 changes in rainfall on agroecosystems. Consequently, future climate change experiments need
620 to simulate more realistic climate change scenarios and consider increases of temperatures,
621 precipitation and CO₂ combined. A more exhaustive examination of climate change
622 consequences on agricultural ecosystems through a combined approach using ENA and DNA-
623 based methods is the fundamental first step to predict the impact of global changes on food
624 production.

625

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635

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972 **Data accessibility**

973 DNA sequences were assigned Genbank accession numbers: MF154009 – MF154409
974 Plot level plant, insect and network data is available on Dryad: doi:10.5061/dryad.80vd7q6

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976 **Author contributions**

977 DME designed the project. SAPD and SCFB performed the field sampling. SAPD and DHL
978 developed the molecular methodology. SAPD, SCFB and PCN performed the molecular work
979 in the laboratory. EDM processed the crop yield data. SAPD and DME analysed the data.
980 SAPD and DME wrote the first draft of the manuscript, all authors contributed substantially to
981 revisions.

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983 **Supporting information**

984 Additional supporting information may be found in the online version of this article.

985 Figure S1 Experimental layout of the simulated climate change experiment at Stockbridge
986 Technology Centre, North Yorkshire, UK.

987 Table S1 Qualitative network descriptors (LD, C, G, V) and unweighted quantitative network
988 descriptors (LD'q, C'q, G'q, V'q) for each treatment (mean \pm standard deviation).

989 **Tables and figure captions**

990

991 **Table 1.** Trophic-level descriptors for each treatment (mean \pm standard deviation). Descriptors were calculated for each of the 24 experimental
 992 plots and then compared between treatments. Effects of treatments on descriptors were tested with GLM (Family Gaussian, F-test; except for Aphid
 993 abundances: family Poisson; Chi-square test). W+P: warming and precipitation; \uparrow P: increase in precipitation; \uparrow T $^\circ$: increase in temperature.
 994 Significant effects at α of 0.05 are in bold.

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	Plant richness	Weed Cover	Wheat Cover	Aphid richness	Aphid abundance	Wheat aphid abundance	Parasitism rate	Multiparasitism rate	Hyperparasitism rate	Parasitoid richness	Total species richness
Control	2 \pm 0.632	20.5 \pm 4.806	77.167 \pm 4.215	2.667 \pm 1.033	46.167 \pm 19.682	31.167 \pm 7.494	0.339 \pm 0.077	0.037 \pm 0.038	0.082 \pm 0.072	8.333 \pm 2.16	12.833 \pm 3.488
Precipitation	1.667 \pm 0.816	19 \pm 4.195	78.833 \pm 1.602	2.167 \pm 0.753	59.667 \pm 55.479	36 \pm 13.387	0.347 \pm 0.111	0.042 \pm 0.028	0.063 \pm 0.053	7.833 \pm 1.472	11.667 \pm 2.066
Warming	2.667 \pm 1.033	33.333 \pm 16.525	62.5 \pm 14.053	2.833 \pm 0.753	183.333 \pm 109.485	86.333 \pm 49.443	0.39 \pm 0.093	0.041 \pm 0.014	0.067 \pm 0.033	7.833 \pm 1.941	13.333 \pm 3.077
W+P	1.833 \pm 0.753	24.5 \pm 10.635	68.333 \pm 10.801	2.667 \pm 0.816	286.167 \pm 267.655	97.167 \pm 55.315	0.362 \pm 0.067	0.031 \pm 0.023	0.084 \pm 0.044	5.5 \pm 0.548	10 \pm 1.265
\uparrow P F-value	3.09	1.519	1.043	0.966			0.079	0.082	0.044	4.247	4.413
\uparrow P p-value	0.093	0.231	0.319	0.337	<0.001	0.609	0.782	0.777	0.948	0.052	0.048
\uparrow T $^\circ$ F-value	1.577	4.78	11.746	0.966			0.851	0.091	0.02	4.247	0.297
\uparrow T $^\circ$ p-value	0.223	0.04	0.003	0.337	<0.001	0.009	0.367	0.766	0.889	0.052	0.592

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999 **Table 2.** Weighted quantitative network descriptors (LDq, Cq, Gq) of tri-partite networks and bipartite (plant-aphid and aphid-parasitoid) networks
 1000 for each treatment (mean \pm standard deviation). Vq and IEq are presented in Figure 2. Network descriptors were calculated for each of the 24
 1001 networks and then compared to each other. Effects of treatments on network descriptors were tested with GLM (Family Gaussian; F-test). W+P:
 1002 warming and precipitation; \uparrow P: increase in precipitation; \uparrow T $^\circ$: increase in temperature; sd: standard deviation. Significant effects at a Bonferroni-
 1003 corrected α of 0.001 are in bold.
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	Plant-aphid-parasitoid networks			Plant-aphid networks			Aphid-parasitoid networks		
	LDq	Cq	Gq	LDq	Cq	Gq	LDq	Cq	Gq
Control	1.945 \pm 0.452	0.157 \pm 0.045	1.142 \pm 0.1	1.284 \pm 0.175	0.297 \pm 0.085	1.111 \pm 0.183	3.305 \pm 0.828	0.317 \pm 0.095	1.231 \pm 0.163
Precipitation	1.978 \pm 0.22	0.175 \pm 0.039	1.197 \pm 0.201	1.322 \pm 0.197	0.380 \pm 0.104	1.164 \pm 0.234	3.445 \pm 0.504	0.354 \pm 0.072	1.266 \pm 0.174
Warming	1.593 \pm 0.208	0.125 \pm 0.035	1.131 \pm 0.093	1.223 \pm 0.116	0.245 \pm 0.096	1.113 \pm 0.123	2.369 \pm 0.579	0.228 \pm 0.056	1.170 \pm 0.124
Warming+Precipitation	1.589 \pm 0.136	0.162 \pm 0.028	1.159 \pm 0.128	1.251 \pm 0.11	0.306 \pm 0.094	1.066 \pm 0.148	2.307 \pm 0.221	0.285 \pm 0.042	1.361 \pm 0.185
\uparrow P F-value	0.015	2.789	0.474	0.239	3.018	0.002	0.024	2.409	2.373
\uparrow P p-value	0.905	0.11	0.499	0.63	0.097	0.966	0.878	0.136	0.138
\uparrow T $^\circ$ F-value	9.168	1.859	0.161	0.944	2.284	0.37	16.985	6.724	0.053
\uparrow T $^\circ$ p-value	0.006	0.187	0.693	0.342	0.146	0.549	< 0.001	0.017	0.821

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1009 **Table 3.** Impact of the simulated climate-change on the wheat: number of seeds / ear, total seed weight per ear (g), density of wheat (number of
 1010 wheat plants / m²) and crop yield (g / m²) for each treatment (mean ± standard error). Measurements of *T. aestivum* were calculated for each of the
 1011 24 experimental plots and then compared to each other. Effects of treatments were tested with GLM (Family Gaussian; F-test; non-crop cover and
 1012 pest aphid abundance were not included in these models). Significant effects (p < 0.05) are in bold.
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	Number of seeds	Seed weight / ear (g)	Density of wheat	Yield (g/m ²)
Control mean ± se	46.67 ± 1.72	2.46 ± 0.11	534.7 ± 57.5	1323.7 ± 192.4
Precipitation mean ± se	44.5 ± 2.18	2.37 ± 0.12	519.3 ± 27.5	1239.3 ± 97
Warming mean ± se	40.77 ± 1.7	2.1 ± 0.11	401.3 ± 82.4	872.5 ± 209.7
W+P mean ± se	42.7 ± 1.81	2.14 ± 0.12	478.7 ± 61.5	1024.8 ± 167.7
↑Precipitation F-value	0.0039	0.0166	0.2677	0.0399
↑Precipitation p-value	0.9502	0.8509	0.6103	0.8435
↑Warming F-value	4.2722	3.0485	2.1088	3.8351
↑Warming p-value	0.0410	0.0119	0.1612	0.0636

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1016 **Table 4.** Effect of treatments and covariates on the density of wheat (number of wheat plants /
 1017 m²) and on the crop yield (g/m²). Warming treatment, precipitation treatment and non-crop
 1018 cover were included in a single GLM (Family Gaussian; F-test) when assessing their effects
 1019 on wheat density. Warming treatment, precipitation treatment and pest aphid abundance were
 1020 included in a single GLM (Family Gaussian; F-test) when assessing their effects on crop yield.
 1021 Significant effects (p < 0.05) are in bold.
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	d.f.	Density of wheat		Crop yield (g/m ²)	
		F-value	P-value	F-value	p-value
Warming	1	11.6064	0.002797	6.3304	0.020518
Precipitation	1	1.4736	0.238918	0.0659	0.799986
Non-crop cover	1	95.5818	<0.0001	not included in this GLM	
Wheat aphid abundance	1	not included in this GLM		14.6634	0.001048

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1028 **Table 5.** Generalized linear models comparisons for the density of the wheat (number of wheat
 1029 plants / m²) and the crop yield (g/m²). AIC were calculated for GLMs including only the
 1030 warming and the precipitation treatments (GLM1, models presented in Table 3) and for GLMs
 1031 including warming and precipitation treatments, non-crop cover or wheat aphid abundance as
 1032 covariate (GLM2, models presented in Table 4).
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	AIC GLM1: Treatments only	AIC GLM2: Treatments with covariate
Density of wheat	312.3637	272.2618
Crop yield (g/m ²)	362.4188	351.2199

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1039 **Figure 1.** Impact of simulated climate-change on quantitative ecological plant–aphid–
1040 parasitoid networks. All interactions detected during the sampling season were pooled across
1041 all the plots sharing the same treatment to draw the networks. Interactions related to the crop
1042 are represented in green. Connectivity represents the number of species with which each
1043 species interacts.

1044
1045 **Figure 2.** Impact of climate-change on weighted quantitative vulnerability V_q and interaction
1046 evenness IE_q for tri-partite and bipartite networks. Different letters indicated a significant
1047 difference at a Bonferroni-corrected α of 0.01. Impact of treatments on the network descriptors
1048 was tested in distinct Generalized Linear models.

1049
1050 **Figure 3.** Impact of the simulated climate-change on the crop yield (g/m^2). The effects of the
1051 treatments on the crop yield were tested with a Generalized Linear model (pest aphid
1052 abundance included as covariate in the model).