1	Climate-warming alters the structure of farmland tri-trophic ecological networks and
2	reduces crop yield
3	
4	Stephane A.P. Derocles ^{1,2} , David H. Lunt ² , Sophie C.F. Berthe ² , Paul C. Nichols ² , Ellen D.
5	Moss ^{2,3} , Darren M. Evans ^{2,3}
6	
7	¹ INRA, UMR 1347 Agroécologie, BP 86510, F-21000, Dijon, France
8	² School of Environmental Sciences, University of Hull, Hull HU6 7RX, UK
9	³ School of Natural and Environmental Sciences, Newcastle University, Newcastle upon Tyne NE1
10	7RU, United Kingdom
11	
12	Keywords: Food-webs, global warming, DNA-barcoding, ecosystem services, natural pest
13	control, food security.
14	
15	Corresponding author: Darren Evans; E-mail: darren.evans@ncl.ac.uk; Phone: +44 (0)191
16	2083043
17	
18	Running title: Climate-warming alters ecological networks
19	
20	
21	
22	
23	

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

48

49

50 Introduction

Climate change is expected to have profound impacts on food production systems over the coming 51 52 decades (Lobell et al. 2008). Crops will be adversely affected by a combination of both abiotic (e.g. heat, drought, salinity and submergence in water) and biotic (e.g. pests and pathogens) 53 stresses (Baulcombe et al. 2009; Maxmen 2013; Bebber et al. 2014; Lesk et al. 2016), posing 54 55 significant threats to food security (Godfray et al. 2010). Despite the growing research demonstrating the impacts of climate change on species abundances and distributions, community 56 composition and organismal physiology (Sala et al. 2000; Parmesan 2006; Garcia et al. 2014), 57 climate change effects on the networks of interactions among species are poorly understood 58 (Tylianakis et al., 2008), particularly in agro-ecosystems. This is largely due to the difficulties in 59 quantifying changes in interactions compared with changes in biodiversity (McCann 2007). Yet, 60 complex networks of biotic interactions, such as insect pollination and parasitism, play an 61 important role in the maintenance of biodiversity (Bascompte et al. 2006), provide valuable 62 63 ecosystem services (Pocock et al., 2012), and can mediate ecosystem responses to environmental change (Sydes & Miller 1988; Brooker 2006). Species-interactions may, however, be more 64 susceptible to climate change, as they are sensitive to the phenology, behaviour, physiology and 65 66 relative abundances of multiple species (Memmott et al. 2007; Suttle et al. 2007; Tylianakis et al. 2007). 67

Combining advances in both network theory and molecular ecology offers unprecedented 69 opportunities to describe interactions between species, the structure of communities and the 70 function and stability of ecosystems (Evans et al. 2016). Ecological networks provide a 71 quantitative framework to unify the study of biodiversity and ecosystem function (Thompson et 72 al. 2012) and have been successfully used to quantity the ecosystem-level consequences of global 73 74 environmental change (Tylianakis et al. 2010). There is growing interest in developing these approaches to provide a more holistic, systems-based understanding of agro-ecosystems that could 75 be used to maximise the ecosystem services provided by farmland biodiversity, as well as for 76 77 anticipating and mitigating future scenarios (Bohan et al. 2013). For example, Macfadyen et al. (2009) constructed quantitative plant-herbivore-parasitoid networks on paired organic and 78 conventional farms and showed that the organic farms had more species across the three trophic 79 levels and significantly different network structure. However, such networks take considerable 80 effort to construct and can be subject to bias because of the limitations of taxonomically selective 81 rearing success as well as the reliance on accurate morphological identification (Evans et al. 2016). 82 Advances in DNA sequencing technologies provide enormous potential to determine hitherto 83 difficult to observe species interactions and thus to produce highly-resolved ecological networks 84 (Wirta et al. 2014; Derocles et al. 2018; Evans et al. 2016). An accurate and cost-effective PCR 85 diagnostics approach has recently been developed to allow the rapid construction of quantitative 86 ecological networks of farmland aphid-parasitoid interactions (Derocles et al. 2012a, 2014) 87 88 providing new opportunities to examine the impacts of environmental change on network structure and complexity. 89

90

91 In northern Europe, climate models predict significant warming and an increase in both

precipitation (mainly in winter) and the frequency of extreme weather events (IPCC 2014), which 92 are likely to cause significant damage to agro-ecosystems (Olesen et al. 2011). With increasing 93 evidence that present climate change is altering geographical ranges, population dynamics and 94 phenologies of some insects (Altermatt 2010; Morris et al. 2015), there is growing concern that 95 global food security is threatened by the emergence and spread of crop pests and pathogens 96 97 (Maxmen 2013). Given the ecological and economic importance of phytophagous insects and their natural enemies, a greater understanding of their direct and indirect interactions and how these 98 respond to experimental manipulation is needed (van Veen et al. 2006), particularly in the context 99 100 of climate-warming.

101

Experimental manipulations of temperature and precipitation have provided important insights 102 103 into the responses of terrestrial ecosystems, with climate-warming generally stimulating total net primary productivity, increasing ecosystem photosynthesis and respiration (see Wu et al. 2011 for 104 a review). Real-world experimental climate manipulations can help to fill the knowledge gap 105 between highly controlled, closed-system laboratory studies (e.g. Le Lann et al. 2014) that tend to 106 focus on a small number of species, and large scale open-field experiments that rely on variations 107 108 in temperature along environmental gradients (see de Sassi & Tylianakis 2012; Romo & Tylianakis 2013). To date, most field-based simulated-warming experiments have used infrared heating 109 devices (see de Sassi et al. (2012) who used underground heating cables) but have mainly focused 110 111 on plant responses to elevated temperatures. To our knowledge, none have examined the impacts on networks of interacting species across multiple trophic levels. Within grasslands, de Sassi & 112 Tylianakis (2012) demonstrated that in a tri-trophic system of plants, herbivores and parasitoids, 113 114 each trophic level responded differently to warming and overall the community was increasingly

dominated by herbivores. Within arable crops, a small number of individual simulated climate-115 warming studies have demonstrated a reduction in wheat yield (Fang et al. 2013) and increases in 116 aphid pests (Dong et al. 2013) and insect predators (Berthe et al. 2015). Thus it is unlikely that 117 climate-warming will affect species richness within arable crops, rather it will alter network 118 structure and complexity, in particular consumer-resource asymmetries (e.g. network 'generality' 119 120 - the mean effective number of lower trophic level species per higher trophic level species) and interaction evenness, driven by changes in the abundances and frequency of interactions between 121 plants, aphids and parasitoids. However, predicting the specific impacts on the complex pattern of 122 123 interactions among species in a community remains a pressing challenge (Staniczenko et al. 2017).

124

Here, we experimentally increase temperature and rainwater within farmland plots consisting of 125 126 spring-sown wheat and common uncultivated plant (weed) species. The study is framed in the context of understanding climate change implications as it relates to policy targets (e.g., limiting 127 warming to 2°C) within North European agriculture (Olesen et al. 2011). We examine the 128 responses of quantitative plant-aphid-parasitoid networks, constructed using DNA-based methods, 129 as well as the impacts on crop yield. Although predicting the direct and indirect responses of plants, 130 131 phytophagous insects and their natural enemies to perturbation is a major challenge, quantitative ecological networks are particularly well suited for assessing direct and indirect interactions in the 132 first instance (van Veen et al., 2006). Our objectives are threefold. (1) To construct replicated, 133 134 quantitative tri-partite food-webs describing the interactions between crop and non-crop plants, aphids and parasitoids. We apply a DNA-barcoding approach to accurately and cost-effectively 135 quantify the interactions of Aphidiinae endoparasitoids with their aphid hosts. (2) To examine the 136 137 combined effects of a 1.4°C temperature elevation and increase in rainwater on measures of

network structure and complexity. We use suspended infrared heaters, which have been effectively 138 applied in other habitats for climate change simulation experiments (Price & Waser 2000; Wan et 139 al. 2002; Harte et al. 2015) to warm farmland plots in situ, and apply extra rainwater following 140 established protocols (Rollinson & Kaye 2012). We predict no impacts on total species richness, 141 but significant increases in aphid abundances in warmed plots due to a positive direct effect on 142 population growth rate (Barton & Ives 2014) and a corresponding increase in the frequency of 143 parasitoid interactions, potentially leading to changes in network consumer-resource asymmetries 144 and interaction evenness. As aphids and parasitoids are highly specialized in agro-ecosystems (Le 145 146 Ralec et al. 2011; Derocles et al. 2014), we do not expect an increase in network connectance (a measure involving the number of interactions) in the short-term, as this would indicate an 147 expansion of generalism of the species involved. We test this for both bipartite and tripartite 148 networks. (3) To investigate the overall effects of warming on crop yield and whether any changes 149 can be mediated by an increase in rainwater (either as precipitation or as added irrigation). 150

151

152 MATERIALS AND METHODS

153 Experimental layout

The study was conducted in 2013 at Stockbridge Technology Centre (STC), North Yorkshire, UK (53°49' N -1°9' W), a conventional farm consisting of meadows and cereal crops used for field experiments. The climate is temperate oceanic, with a mean minimum and maximum annual temperature and precipitation of 5.5–14°C (8.6–19.1 °C during the experiment) and 537.7 mm (156.6 mm during the experiment) respectively. We established a replicated, randomized block open-field experiment consisting of six replicates of four simulated climate change treatments in a field of spring wheat (*Triticum aestivum* cultivar Tybalt) (see Berthe *et al.* 2015, Figure S1,

Supporting information). The four treatments consisted of: (W) 1.4°C increase in temperature; (P) 161 10% increase in precipitation/rainwater per week, based on historic records; (WP) warming and 162 precipitation treatments combined; and (C) control (ambient conditions). We refer to "climate-163 warming" when reporting the effect of warmed treatments and "precipitation" when reporting the 164 effect of additional rainwater treatments. Treatments were randomly allocated to 2×2 m 165 experimental plots that were each separated by 2 m of wheat to provide a buffer and allow the free 166 movement of insects. The W and WP treatments involved suspending 240 V infrared heaters 1.5 167 m above each plot (following Rollinson & Kaye 2012), consistently heating throughout the day 168 169 and night: this primarily drives plant phenology rather than heating the column of air (Kimball 2005; White et al. 2011). A 'dummy' heater of the same size and shape was suspended in the non-170 heated plots to account for any possible effects of shading/shelter. 171

172

A real-time proportional-integrative-derivative feedback system ensured constant temperature plot 173 warming through infrared radiometer (IRR) monitoring of surface temperatures in warmed plots. 174 Soil-surface temperatures were monitored by 6 Infrared Remote Temperature Sensors (IR120; 175 Campbell Scientific; Loughborough, UK), positioned 1.10 m above the plots and directed to the 176 middle of the plot and connected to a data logger (Campbell Scientific; Loughborough, UK) to 177 record the temperatures every 10s and to control the constant output of the infrared heaters. Their 178 positions were selected randomly, three within a heated plot (W, WP) and three within an unheated 179 180 plot (C, P). Our original aim was for the system to increase the temperature in the warmed plots by 2°C. Over the course of the experiment, temperatures were raised, on average, by 2.2°C 181 (standard deviation 0.6) in block 1; 1.1°C in block 2 (standard deviation 0.6) and 1.1°C in block 3 182 183 (standard deviation 0.8) that most likely reflected subtle microclimate differences within the field.

This provided a mean temperature increase of 1.4°C (standard deviation 0.9) across all the plots. 184 Increased rainwater was simulated in the P and WP plots by manually adding 10% extra collected 185 rainwater each week based on STC mean monthly rainfall data collected between 2002 and 2012. 186 This can either be interpreted as representing weather conditions in a warm and wet summer, or a 187 farmer increasing irrigation to mitigate the effects of a warm and drier summer. We added the 188 following water each week: 13 L in April; 19 L in May; 24 L in June; 26 L in July and 30 L in 189 August, amounting to 407 L in total for each plot. During the course of the experiment, just 156.6 190 mm of rainfall was measured at Stockbridge Technology Centre, well below the annual average. 191 192 Thus we actually increased precipitation/rainwater by 40% that year. The experimental area in which the plots were located received herbicide applications on 2nd April and 13th May 193 (pendimethalin; metsulfuron-methyl and thifensulfuron-methyl); our aim was to allow some weed 194 growth without out-competing the wheat. Experimental treatments commenced immediately after 195 the sowing of spring wheat on 13th April and stopped with the harvest of the crop on 16th August. 196

197

198 *Plant surveys and crop yield*

Plants were identified to the species level, with a small proportion to the genus or family, and the 199 percentage cover of each was recorded weekly (18 surveys) in each plot. The date of emergence 200 of the first leaf and the date of emergence of the first ear for *T. aestivum* was recorded in each plot 201 and converted into Julian date for statistical analysis. At harvest, a 0.5×0.5m quadrat was placed 202 203 in the area directly below the heaters/dummy heaters (we selected this area because the heating pattern is likely to be more consistent; Kimball 2005) and the number of *T. aestivum* ears counted. 204 The density of wheat (number of wheat ears m⁻²) was then calculated for each plot. We also 205 206 harvested five ears randomly from each plot, which were dried in an oven at 80°C for 48 hours in

the laboratory. The seeds were counted and the total seed weight was measured for each ear. For

each plot, crop yield (g/m^2) was calculated as: (total seed weight / ear) x density of wheat.

209

210 Insect surveys

Plant-aphid interactions were recorded by systematically searching each plot and counting the total 211 number of aphids and visibly parasitized aphids ('mummies') on each plant species every week 212 (18 surveys) throughout the sampling period. We collected up to 30 aphid individuals per colony 213 and placed them in a 1.5ml tube filled with 95% ethanol and then stored at -20 °C in the laboratory 214 215 for later identification (see below). All aphid mummies were collected and stored in 1.5ml tubes, but without 95% ethanol. Instead, these were stored under laboratory conditions and observed for 216 10 days for the emergence of adult parasitoids. Adult parasitoids and aphid mummies where 217 parasitoids did not emerge were then stored individually in a 1.5ml tube filled with 95% ethanol 218 at -20 °C. 219

220

221 *Insect identification*

Aphids were first identified morphologically following Blackman & Eastop (1994, 2000, 2006). 222 We extracted the DNA of all the aphids collected using a hotshot DNA extraction (Montero-Pau 223 et al., 2008). Aphid identification was confirmed with DNA barcoding: a fragment 658 bp from 224 Cytochrome C oxidase subunit I [COI] was amplified and sequenced with the PCR conditions 225 226 described by Derocles et al. (2012b) and the following primer pairs: LCO1490 (5'-GGTCAACAAATCATAAAGATATTGG-3'; Folmer et al. 1994) and the degenerate reverse 227 primer HCO2198-puc (5'-TAAACTTCWGGRTGWCCAAARAATC-3'; Cruaud et al. 2010). 228 229 Adult parasitoids and non-emerged parasitoids from the mummies (n = 181) were identified using

the DNA barcoding tool described by Derocles et al. (2012b): a fragment 658 bp from COI was 230 amplified and sequenced to identify these parasitoids. Aphid-parasitoid interactions and parasitism 231 rates were determined using two different molecular methods based on the extracted DNA of 232 aphids. First, we used a multiplex PCR approach developed by Traugott et al. (2008) on the aphid 233 species collected on T. aestivum (Sitobion avenae and Metopolophium dirhodum) to detect both 234 primary and secondary parasitoids. We used nine primary parasitoid and two hyperparasitoid 235 species-specific primer pairs to detect and identify immature primary and secondary parasitoids 236 within cereal aphid hosts. Second, for all the other aphid species, we used the approach developed 237 238 by Derocles et al. (2012a) that uses the sequences of a 210 bp fragment from the 16S gene to identify to species-level (in most cases) the immature Aphidiinae parasitoids within an aphid host. 239 To improve the reliability, we added an 'in tube control' to determine if an absence of parasitoid 240 detection is due to either a true absence of parasitism or a technical problem during DNA extraction 241 or PCR amplification. For this, we followed the PCR protocol for parasitoid detection described 242 by Derocles et al. (2012a) and we added in the PCR-mix the aphid COI barcode assay described 243 above. A detection of a parasitoid within an aphid host is characterized by two bands on a 1.5% 244 agarose electrophoresis gel: a band of 658 bp (COI, aphid and parsitoid) and a band of 210 bp (16S 245 parasitoid); an unparasitized aphid is characterised only by the band of 658 bp, from the aphid 246 DNA. An absence of band indicates a failure from either the DNA extraction or the PCR 247 amplification. In this case, the PCR amplification is performed a second time. If after a second 248 249 PCR amplification a failure is observed, the individual is removed from the analysis. Sixteen aphids were removed from the analysis following two PCR failures. We used two hyperparasitoid 250 251 species-specific primer pairs (Traugott et al. 2008) to detect the secondary parasitoids in non-crop 252 aphid species. We compared parasitism rate determined using this method versus the conventional

253	approa	ch (i.e. the number of aphid mummies collected) / (number of aphid counted).
254		
255	Insect	abundance, species richness and parasitism rates
256	For ea	ch plot, we pooled data across the sampling period to calculate:
257	1)	percentage of aphids sampled: number of aphids sampled / number of aphids counted
258	2)	aphid abundance: total number of aphids counted on each plant species throughout the
259		sampling period
260	3)	total species richness
261	4)	species richness per trophic level (i.e. plants, aphids, parasitoids)
262	5)	parasitism rate using the DNA-based method: (the number of aphid mummies collected +
263		number of parasitised aphids detected) / (number of aphid mummies collected + number
264		of aphids collected);
265	6)	parasitism rate using the conventional method (no DNA-based method): (the number of
266		aphid mummies collected) / (number of aphid counted);
267	7)	multiparasitism rate using the DNA-based method: (number of aphids parasitised by at
268		least two detected primary parasitoid species / number of aphids collected + number of
269		mummies collected)
270	8)	hyperparasitism rate using the DNA-based method: (number of aphids parasitised by a
271		secondary parasitoid + number of secondary parasitoids identified in mummies / number
272		of aphids collected + number of mummies collected).
273		

274 *Ecological network construction, visualisation and description*

275 Plant-aphid-parasitoid quantitative networks were constructed for each plot by pooling data

276 collected during the course of the experiment. We visualised the tripartite interactions for each of the four treatments (by pooling replicate data from replicate plot) using the "HiveR" package 277 (Krzywinski et al. 2011) in R 3.3.1 (R Core Team, 2016). We were particularly interested in how 278 the experimental treatments affects consumer-resource asymmetries, classically described in 279 network ecology as vulnerability and generality (i.e. the mean number of consumers per prey, and 280 the mean number of prey per consumer, respectively), as well as standard measures of complexity 281 (Bersier et al. 2002). They are well suited for describing antagonistic interactions and the extent 282 to which consumers are specialized to the resource and how the resource is attacked by the higher 283 284 trophic level (Wirta et al. 2014). For each of the 24 tripartite networks, we calculated the following qualitative, unweighted quantitative and weighted quantitative network descriptors described by 285 Bersier et al. (2002) using 'cheddar' (Hudson et al. 2013) and 'bipartite' packages in R 3.3.1 286 (Dormann *et al.* 2009): Link density (average number of links per species: LD, LD'q, LDq); 287 Connectance (proportion of possible links between species that are realized: C, C'q, Cq); 288 Vulnerability (mean effective number of higher trophic level species per lower level species: V, 289 V'q, Vq) and Generality (mean effective number of lower trophic level species per higher trophic 290 level species: G, G'q, Gq). We based our analysis on weighted quantitative network descriptors 291 (LDq, Cq, Vq and Gq) to specifically examine changes in network complexity and consumer-292 resource asymmetries as they are commonly used in ecological network studies and less prone to 293 sampling biases (Tylianakis et al. 2007; Macfadyen et al., 2009; Wirta et al. 2014). As interaction 294 295 evenness may be ecologically important, and that these network descriptors are relatively insensitive to differences in the evenness of the distribution of link magnitude, we calculated the 296 quantitative tri-partite interaction evenness (IEq) following Albrecht et al. (2007). To examine 297 298 whether plant-herbivore and herbivore-parasitoid interactions react differently to climate change,

we also calculated network descriptors for the plant-aphid and aphid-parasitoid bipartite networksseparately.

301

302 Statistical analysis

Statistical analysis was performed in R 3.3.1 (R Core Team, 2016). The effects of treatment on the 303 304 plants (including yield), insects, parasitism rates and network descriptor response variables were examined using Generalized Linear Models (GLM) with a Gaussian family (except for aphid 305 abundance data, where a Poisson family was used). To account for the intercorrelation between 306 307 the network descriptors, and to reduce the probability of a type I error, we used a Bonferronicorrected α of 0.01 to assess the level of significance for the five network descriptors (*i.e.* LDq, 308 Cq, Vq, Gq and IEq, following Tylianakis et al. 2007). This correction was used when assessing 309 the effect of treatments on tri-partite network descriptors and on bipartite (plant-aphid and aphid-310 parasitoid) network descriptors. 311

312

The effects of treatment on the crop phenology (Julian dates of emergences of first leaf and first 313 ear) were examined with Mann-Whitney tests. The effects of treatment on the crop (i.e. number of 314 seeds / ear, the seed weight / ear, the density of wheat and yield) were examined using GLM with 315 a Gaussian family. In addition to the climatic treatments, biological interactions may also affect 316 the crop yield (see Gagic et al. 2016). Non-crop plants are competitors for space and resources 317 318 with the crop (Fahad et al. 2015). Sitobion avenae and Metopolophium dirhodum are aphid species feeding on the wheat which may alter the yield (van Emden & Harrington 2007). In order to 319 320 examine the potential impact of uncultivated plants on the density of the wheat, a second GLM 321 was performed with the percent cover of non-crop plants included as a covariate. Similarly, when

analysing the yield data, we included the abundance of wheat aphids *S. avenae* and *M. dirhodum* as a covariate in a separate model and compared the model fit with and without the covariates using Akaike Information Criteria (AIC). In summary, we compared the AIC of the following models:

- a) the effect of precipitation and increased temperatures on the density of the wheat versus
 the effect of precipitation, increased temperatures and percent cover of non-crop plants on
 the density of the wheat;
- b) the effect of precipitation and increased temperatures on the crop yield versus the effect of
 precipitation, increased temperatures and the abundance of wheat aphids on the crop yield.
- In addition, ANOVA was performed on these two model comparisons to test whether the inclusionof covariates provided a significantly better fit to the model.
- 333

334 **Results**

335 We quantified 2836 interactions between eight plant species (6 plants identified to species level, 1 to the genus level and 1 to the family level), 1946 aphids (1765 living aphids and 181 aphid 336 mummies) belonging to six species, 761 primary parasitoids from 13 species and 129 secondary 337 parasitoids from two species. Of the 129 secondary parasitoids identified, only 41 primary 338 parasitoid - secondary parasitoid interactions were recovered. Consequently, primary and 339 secondary parasitoids were considered as belonging to the same trophic level and separate primary 340 parasitoid – secondary parasitoid interactions were not examined (Figure 1). Overall, the 1946 341 aphids included in the ecological network analysis represented 56.3% of the total aphids counted 342 343 in the experimental plots.

345 Plant cover and richness

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

352

353 *Aphid abundance and parasitism rates*

We found no effect of treatment on aphid species richness, but climate-warming resulted in 354 significant aphid outbreaks (GLM, df = 1, p < 0.001; Table 1), with four times as many aphids in 355 the warmed plots compared to control plots. The abundance of the wheat aphids S. avenae and M. 356 *dirhodum* doubled as a result of warming (GLM, df = 1, p = 0.009; Figure 1, Table 1). Molecular 357 analyses revealed high rates of parasitism (based on parasitoid detection within aphids and 358 mummies sampled; mean $36 \pm 1.7\%$) compared to the conventional 'mummy' collection/rearing 359 method (based solely only on mummies sampled; mean $9.9 \pm 1.8\%$). Climate-warming did not 360 significantly change parasitoid species richness, although we did detect a trend (GLM, df = 1, F =361 4.247, p = 0.052). There were no significant effects of treatment on parasitism rates nor 362 multiparasitism (two primary parasitoids within a single aphid) and hyperparasitism rates (aphids 363 364 parasitised by secondary parasitoids), which were relatively low across the treatments $(3.77 \pm$ 0.01% and $7.38 \pm 0.01\%$ respectively; Table 1). 365

366

367 *Tripartite ecological network structure*

We found a significant effect of climate-warming on total species richness across trophic levels 368 (Table 1, Figure 1). Precipitation did not affect quantitative tripartite network descriptors Vq 369 (GLM, F = 0.003, df = 1, p = 0.959), IEq (GLM, F = 0.274, df = 1, p = 0.606; Figure 2), LDq, Cq 370 and Gq (Table 2). Simulated climate-warming did not affect qualitative network descriptors (Table 371 S1), however it did significantly decrease quantitative tripartite Vq (GLM, F = 10.063, df = 1, p =372 0.005; Figure 2) and LDq, but did not affect Cq, Gq (Table 2) and IEq (GLM, F = 0.362, df = 1, p 373 = 0.554; Figure 2). Within the 24 networks, both aphids and parasitoids never consumed more than 374 three different species from the lower trophic level (Figure 1). 375

376

377 *Plant-aphid bipartite network structure*

Precipitation did not affect plant-aphid quantitative network descriptors Vq (GLM, F = 0.425, df = 1, p = 0.522), IEq (GLM, F = 0.0001, df = 1, p = 0.991; Figure 2), LDq, Cq and Gq (Table 2). Likewise, climate-warming did not affect plant-aphid quantitative network descriptors Vq (GLM, F = 0.753, df = 1, p = 0.395), IEq (GLM, F = 5.574, df = 1, p < 0.029; Figure 2), LDq, Cq and Gq (Table 2)

383

384 *Aphid-parasitoid ecological network structure*

Precipitation did not affect aphid-parasitoid quantitative network descriptors Vq (GLM, F = 0.005, df = 1, p = 0.944), IEq (GLM, F = 1.091, df = 1, p = 0.308; Figure 2), LDq, Cq and Gq (Table 2). However, climate-warming significantly decreased aphid-parasitoid quantitative network descriptors Vq (GLM, F = 18.456, df = 1, p < 0.001) and LDq, but did not affect Cq and Gq. Climate-warming negatively affected aphid-parasitoid IEq (GLM, F = 37.599, df = 1, p < 0.0001). This suggests that higher trophic interactions are more sensitive in our system and was likely caused by an increase in the frequency of interactions between wheat aphids and two primary
parasitoid species: *Aphidius rhopalosiphi* and *Aphidius ervi*.

393

394 Wheat phenology

First leaves emerged three days earlier in the warmed plots (Mann-Whitney, W = 118, p = 0.002).

First ears emerged eleven days earlier on average in the warmed plots (Mann-Whitney W = 144,

p < 0.001). Precipitation affected neither the emergence of the first leaves (Mann-Whitney, W =

398 63.5, p = 0.586) nor the first ears (Mann-Whitney, W = 72, p = 1).

399

400 *Crop yield*

Climate-warming significantly reduced the seed number (GLM, F = 4.272, df = 1, p = 0.041, Table 401 3), the seed weight (GLM, F = 3.049, df = 1, p = 0.012; Table 3) but not the density of the wheat 402 (GLM, F = 2.109 df = 1; p = 0.161; Table 3), resulting in no overall reduction in crop yield (GLM, 403 F = 3.835, df = 1, p = 0.064; Table 3). However, when including the detrimental effect of non-crop 404 plants or wheat aphid abundance in the models, we found a significant decrease in wheat density 405 (GLM, F = 11.606, df = 1, p = 0.003; Table 4) and crop yield (GLM, F = 6.33, p = 0.021, df = 1; 406 Figure 3; Table 4). Yield loss was not compensated by increased rainfall (GLM, F = 0.066, df = 1; 407 p = 0.8; Table 4). These models, which including wheat aphid abundances and non-crop cover, 408 provided a significantly better fit to the data than the models considering experimental treatment 409 alone (ANOVA; wheat density: F = 95.582, p < 0.001; crop yield: F = 14.663, df = 1, p = 0.001) 410 Table 5). 411

412

414 **Discussion**

We provide the first experimental evidence, to our knowledge, of the impacts of climate-warming 415 on the structure of tripartite ecological networks, constructed using a DNA-barcoding approach. 416 Experimental warming altered total species richness across trophic levels (but not plant and aphid 417 species richness respectively), it significantly reduced crop percentage cover and substantially 418 increased aphid abundance (the abundance of the economically important aphids S. avenae and M. 419 dirhodum doubled as a result of warming). This affected quantitative network structure and 420 complexity, including aphid-parasitoid interaction evenness. Molecular analyses revealed much 421 422 higher rates of parasitism compared to traditional rearing/identification methods, with generally fewer natural predator species in the warmed plots. However there were no significant effects of 423 treatment on parasitism rates, nor multiparasitism and hyperparasitism. Thus, in the short-term at 424 least, natural pest control (assessed here using a molecular approach to determine parasitism rate) 425 provided by parasitoids appears unaffected, although studies of aphid and parasitoid population 426 dynamics over the long-term are needed. Overall, we show that wheat grown 1.4°C above ambient 427 temperature produced significantly fewer and lighter seeds resulting in a reduction in crop yield, 428 with the best fitting model including aphid abundance and non-crop cover as covariates. We found 429 no statistically significant effect of increased rainwater on any of our response variables, despite 430 it being a very low rainfall season. 431

432

433 *Study limitations*

Despite the advances made by our study, there are important limitations to our experiment. First, the 4 m² plots sampled are not directly comparable to a large cereal crop field. Our results may instead reflect how agricultural communities at field edges respond to climate change. However,

because insect herbivory and parasitism rate are edge-dependent (Maron & Crone 2006; Reeve & 437 Cronin 2010), our results might nevertheless be indicative of the direction of change for plant and 438 animal populations and communities at larger spatial scales as a result of climate-warming, 439 although more research is necessary. Although all simulated climate-warming methods have 440 limitations (Sassi *et al.* 2012), they are nevertheless one of the few tools available in empirically 441 442 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 443 large-scale field experiments and small-scale mesocosms or laboratory experiments (see Romo & 444 445 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 446 how they interact. Thus, conventionally managed cereal crops are likely to have responded 447 differently to the experimental treatments. Third, we only examined the effects of treatment over 448 a single growing season. Further temporal replicates would determine whether the response 449 observed is year-dependent and the extent of interaction turnover (Kemp et al. 2017). Fourth, we 450 did not consider other organisms potentially affecting the plant-aphid-parasitoid networks, such as 451 ants interacting with aphids or predators consuming both aphids and parasitoids (Traugott et al. 452 453 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 454 increasingly possible using the molecular approaches described here and/or Next Generation 455 456 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 457 458 their demographic response to climatic manipulation (*i.e.* treatments affecting population growth 459 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 460 elevated CO₂) are urgently required as well as more detailed observations of host-parasitoid and 461 other predator-prev interactions, although this would need to involve much larger controlled 462 enclosures than are currently available. Finally, we conducted a relatively exhausting sampling 463 where all aphid mummies and more than 50% of aphids were collected for further molecular 464 analyses. Such intensive sampling may certainly affect the aphid and parasitoid population 465 dynamics at the plot-level and could have potentially affected our results. However, adequate 466 network analysis is very dependent on sampling completeness (Blüthgen et al. 2006; Rivera-467 468 Hutinel et al. 2012; Jordano 2016). Consequently, such intensive sampling is well established in studying host-parasitoid interactions (see Traugott et al. 2008) and ecological networks more 469 generally (e.g. Macfadyen et al. 2009) and was therefore necessary for the purposes of this study. 470 Assessing the effect of climate change on aphid and parasitoid dynamics, while also a major issue, 471 would then require a different experimental design. 472

473

474 Trophic level to network level responses

When considering each trophic level separately, climate-warming promoted weed growth 475 (especially Chenopodium album and Cirsium arvense), which increased competition with the crop 476 and contributed to a reduction in crop percentage cover. At the second trophic level, there was a 477 fourfold increase in aphid abundance in the warmed plots, as we predicted, mostly driven by aphids 478 479 associated with T. aestivum. At the third trophic level, contrary to our predictions, parasitism rates remained unchanged. However, a decrease in aphid-parasitoid interaction evenness in the warmed 480 plots suggests that climate-warming might benefit some parasitoid species at the expense of others. 481 482 Whilst both the reduction in crop yield and the aphid pest outbreak followed the general patterns

observed in other recent studies (Maxmen 2013; Dong et al., 2013; Bebber et al. 2014; Liu et al. 483 2016), the significant effects on network structure observed in this study provides new insights 484 into how climate-warming affects entire communities of interacting species. First, we found 485 evidence that climate-warming affects tri-partite consumer-prey asymmetries, with significantly 486 lower network vulnerability and linkage density. Second, connectance was not affected, most 487 likely due to the high trophic specialization for both aphids and associated parasitoid wasps (Le 488 Ralec et al. 2011; Derocles et al. 2014). Third, although there was no effect of treatment on 489 tripartite interaction evenness, climate-warming negatively affected bipartite aphid-parasitoid 490 491 interaction evenness, suggesting that higher trophic interactions might be more sensitive in our system. Indeed, changes in tri-partite network structure are essentially driven by aphid-parasitoid 492 interactions: plant-aphid networks were not affected by simulated-warming while aphid-parasitoid 493 linkage density and vulnerability decreased. Overall, our results support the findings from de Sassi 494 et al. (2012) showing that climate-warming may have bottom-up effects (on host density and body 495 size) which can in turn affect the structure of host-parasitoid networks. 496

497

498 Parasitism

We found no effect of climate-warming on the parasitism rate and species richness of parasitoid wasps (although precipitation and warming treatment tended to decrease parasitoid richness) which are intimately linked to the ecosystem service of natural pest control (Traugott *et al.* 2008; Derocles *et al.* 2014). In Northern European agricultural habitats, the most abundant parasitoid species appear more specialized, with reduced attack rates on alternative hosts (Derocles *et al.* 2014). Macfadyen *et al.* (2009) showed significant differences in network structure between organic and conventional farms with more species at three trophic levels (plant, herbivore and

506 parasitoid) on organic farms. Despite herbivores on organic farms being attacked by more parasitoid species, differences in network structure did not affect parasitism rate across a variety 507 of host species. In our study, climate-warming mainly influenced two parasitoid species, A. 508 rhopalosiphi (the main natural enemy of Sitobion avenae) and A. ervi, driving a decrease in aphid-509 parasitoid interaction evenness. These species differ in their trophic specialization: A. rhopalosiphi 510 511 is a specialist and A. ervi is a generalist (Kavallieratos et al. 2004; Starý 2006). Previous work by Le Lann et al. (2014) under laboratory conditions showed a decrease in the attack rate of A. 512 rhopalosiphi on S. avenae as a result of warming, whereas aphid defense rate increased. Under 513 514 more realistic field-based scenarios, which include a greater range of interacting species, we found the opposite effect. This not only suggests that the degree of specialization may not necessarily 515 explain which species will be more adaptable to environmental changes (as hypothesized by Rand 516 517 & Tscharntke 2007; Tylianakis et al. 2008; Jeffs & Lewis 2013) but that other factors, such as changes in apparent competition (Morris et al. 2004), might be important considerations within a 518 food-web context. Overall, an accurate assessment of natural pest control cannot be undertaken by 519 the single measure of parasitism rate, but would require a careful examination of host and 520 parasitoid population dynamics through further study and a different experimental design. These 521 522 results, together with a recent study by Berthe et al. (2015) at the same study site that showed significant increases in Coleoptera activity-densities but a reduction in community diversity as a 523 524 result of climate-warming, demonstrate the short-term impact of climate-warming on higher 525 trophic levels (i.e. predators and parasitoids) in particular. Given the potential top-down effects driven by these organisms, we expect that climate-warming will result in long-term changes to the 526 527 structure of the ecological network and consequently in natural pest control. Thus long-term 528 climate-manipulation studies across spatial-scales are necessary to better understand the effects of environmental change on agricultural plant-aphid-parasitoid interactions and the ecosystem
service of natural pest control (Cardinale *et al.* 2003; Tylianakis *et al.* 2006; Macfadyen *et al.*2011; Peralta *et al.* 2014).

532

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

534 We found significant effects of climate-warming not only on ecological network structure, but also on crop yield. Experimental-warming has been shown to advance flowering and fruiting phenology 535 for a range of plant species (Sherry et al. 2007; Hovenden et al. 2008; Dong et al. 2013) and in 536 537 our study, first wheat leaves emerged three days earlier on average and ears emerged at least a week earlier in the warmed plots. Wheat grown under experimental-warming produced fewer and 538 lighter grain, resulting in a significant impact on crop yield. There was no significant effect of 539 increased rainwater, which was perhaps surprising given the study was conducted during a very 540 low rainfall season. The yield data from the experiment is nevertheless not directly comparable 541 with commercial agricultural wheat yields. It should be emphasized that it was not our intention 542 to simulate conventional farming methods, where routine spraying would have removed most of 543 the weed species within our plots. Rather we wished to study the community wide response of 544 545 interacting species across trophic levels. In this context, the reduction in crop yield was primarily driven by a combination of the wheat producing fewer, smaller grain as well as increased 546 competition with weed species, rather than significant insect damage (aphid load was very low: 547 548 0.14±0.09 aphids per wheat ear across all plots). Despite this, warming did trigger a fourfold increase in aphid abundance and this is likely to cause significant damage to crops in years when 549 fluctuating aphid numbers are higher. As demonstrated recently by Gagic et al. (2016), attacks by 550 551 several pests can have both positive and negative impacts on crop yield. In our study, crop yield

models produced a better fit when pest aphid abundance was included as a co-variate. However, it still remains unclear how crop (yield in particular) and non-crop plants are affected both directly and indirectly by changes in aphid-parasitoid interactions. By pioneering new molecular methods to construct highly-resolved species-interaction networks, we have provided new, cost-effective tools to examine the response of communities of interacting agricultural species to environmental change.

558

559 Merging DNA-based methods with ecological network analysis

560 Merging molecular methods and ecological network analysis (ENA) provides new tools for understanding ecology and evolution (Raimundo et al. 2018). Here we showed that the detection-561 rate of aphid parasitism was more than three times higher using molecular assays than by 562 563 conventional insect-rearing approaches. Plant-aphid-parasitoid networks, constructed using molecular methods, were more highly-resolved than traditional rearing methods, with significant 564 implications for host-parasitoid network-level analyses (Condon et al. 2014; Hrček & Godfray 565 2015). Traditional approaches based on insect rearing and morphological identification would 566 have failed to detect changes in species interactions mediated by the increase in temperature. 567 Indeed, such approaches rely on the collection of aphid mummies and rearing adults for 568 identification. In our study, only 181 aphid mummies were collected while 709 parasitoids were 569 detected and identified within their living aphid hosts. Parasitism cases using molecular methods 570 571 were therefore able to capture a more exhaustively range of host-parasitoid interactions. These parasitism cases however still need to be considered cautiously: parasitoid eggs or larvae detected 572 do not always achieve their development to the adult stage (Starý et al. 1989). Consequently, 573 574 molecular tools could potentially overestimate parasitism (Traugott et al. 2008). Moreover, aphids

575 collected on the same plant were placed together in a single tube. This may lead to a potential risk 576 of contamination between aphids with parasitoid DNA. But this risk is low because in the same 577 tubes we found both unparasitised and parasitised aphids (from different parasitoid species). 578 Completely eliminating this risk would require each collected aphid to be separately stored but 579 might also result in unrealistic, time-consuming sampling protocols.

580

In summary, this study provides the first evidence, to our knowledge, of the impact of climate 581 change on farmland tri-partite ecological networks, ecosystem services and agricultural output. In 582 583 the short-term, we highlight the potential winners (*i.e.* pests) and losers (*i.e.* pest natural enemies) of agro-ecosystems in a warmer world. Overall, our study provides insights into the potential threat 584 of global warming on both farmland biodiversity and food production. Despite limited changes to 585 586 biodiversity per se, climate-warming affects the frequency of interactions between species, ultimately affecting network structure, although the long-term consequences of altered network 587 structure on ecosystem functioning warrants further study. The detrimental impact of climate-588 warming on wheat suggests the need for adapting future agricultural methods of cropping in 589 response to a climate change (Asseng *et al.*, 2013); cropping methods which in turn can also have 590 591 cascading effects on agro-ecosystems and their networks of interactions. Considering the effects 592 of environmental changes on ecological networks in dynamic models rather than snapshots of communities is essential (Säterberg et al. 2013) as well as taking into account a more complete 593 594 range of interactions (i.e. 'networks of ecological networks'; Pocock et al. 2012; Evans et al. 2013). Future studies should consider the combined effects of climate-warming and elevated CO₂ 595 as the latter also affects wheat growth and grain yield in particular (O'Leary et al. 2015). Such 596 597 changes in plants may also induce bottom-up effects on high trophic levels (e.g. pest arthropods

feeding on the crop). Finally, increased rainwater did not affect the ecological networks and the 598 crop yield in the present study, suggesting that extra water (either as increased precipitation or 599 irrigation) might not mitigate the effects of increased temperature. Further considerations are 600 nevertheless needed to understand the predicted changes in rainfall on agroecosystems. 601 Consequently, future climate change experiments need to simulate more realistic climate change 602 scenarios and consider increases of temperatures, precipitation and CO₂ combined. A more 603 exhaustive examination of climate change consequences on agricultural ecosystems through a 604 combined approach using ENA and DNA-based methods is the fundamental first step to predict 605 606 the impact of global changes on food production.

607

608 Acknowledgements

609 The project was funded by the University of Hull, with support from The Higher Education Innovation Fund (UK). We thank staff at Stockbridge Technology Centre for hosting the 610 611 experiment and for additional help and support. We are grateful to Mike Dennett, Vic Swetez, Aifionn Evans, Stephen P. Moss (all University of Hull, UK) and Bruce A. Kimball (Arid-Land 612 Agricultural Research Center, USDA, Agricultural Research Service, USA) for their in help in 613 614 setting up the experiment. We thank James J.N. Kitson (Newcastle University, UK) for his help with the Hive plots. We are grateful to David A. Bohan (INRA, Agroécologie, Dijon, France) for 615 616 carefully reading and commenting on the manuscript.

617

618 **References**

Albrecht M, Duelli P, Schmid B, Müller CB (2007). Interaction diversity within quantified insect
food webs in restored and adjacent intensively managed meadows. *Journal of Animal Ecology*,
76, 1015-1025.

⁶²³ Altermatt F (2010). Climatic warming increases voltinism in European butterflies and moths.

Proceedings of the Royal Society of London, Series B: Biological sciences, 277, 1281-1287.

624

625 Asseng S, Ewert F, Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, ... Wolf J (2013) 626 Uncertainty in simulating wheat yields under climate change. Nature Climate Change, 3, 827-832. 627 628 Barton BT, Ives AR (2014) Direct and indirect effects of warming on aphids, their predators, and 629 ant mutualists. Ecology, 95, 1479-1484. 630 631 Bascompte J, Jordano P, Olesen JM (2006). Asymmetric coevolutionary networks facilitate 632 biodiversity maintenance. Science, 312, 431-433. 633 634 Baulcombe D, Crute I, David B, Dunwell J, Gale M, Jones J, ... Toulmin C (2009) Reaping the 635 benefits: science and the sustainable intensification of global agriculture. The Royal Society, 636 London, United Kingdom. 637 638 Bebber DP, Holmes T, Gurr SJ (2014) The global spread of crop pests and pathogens. Global 639 Ecology and Biogeography, 23, 1398-1407. 640 641 Bersier LF, Banasek-Richter C, Cattin MF (2002) Quantitative descriptors of food-web matrices. 642 *Ecology*, **83**, 2394-2407. 643 644 Berthe SCF, Derocles SAP, Lunt DH, Kimball BA, Evans DM (2015) Simulated climate-warming 645 646 increases Coleoptera activity-densities and reduces community diversity in a cereal crop. Agriculture, Ecosystems & Environment, 210, 11-14. 647 648 Blackman RL, Eastop VF (1994) Aphids on the world's tree: an identification and information 649 guide. CAB International, Wallingford, Oxon, United Kingdom. 650 651 652 Blackman RL, Eastop VF (2000) Aphids on the world's crop: an identification and information guide. Wiley, Chichester, United Kingdom. 653 654 655 Blackman RL, Eastop VF (2006) Aphids on the world's herbaceous plants and shrubs. Wiley, Chichester, United Kingdom. 656 657 Blüthgen N, Menzel F, Blüthgen N (2006) Measuring spaecialization in species interaction 658 659 networks. BMC Ecology, 6, 9. 660 Bohan DA, Raybould A, Mulder C, Woodward G, Tamaddoni-Nezhad A, Bluthgen N, ... 661 Macfadyen S (2013) Networking Agroecology: Integrating the Diversity of Agroecosystem 662 Interactions. In: Advances in Ecological Research, Vol 49: Ecological Networks in an Agricultural 663 World (eds Woodward G, Bohan DA), pp. 1–67. Academic Press, Amsterdam, The Netherlands. 664 665 Brooker RW (2006) Plant-plant interactions and environmental change. New Phytologist, 171, 666 667 271-284.

668	
669	Cardinale BJ, Harvey CT, Gross K, Ives AR (2003) Biodiversity and biocontrol: emergent impacts
670	of a multi-enemy assemblage on pest suppression and crop yield in an agroecosystem. <i>Ecology</i>
671	<i>Letters</i> , 6 , 857-865.
672	
673	Condon MA, Scheffer SJ, Lewis ML, Wharton R, Adams DC, Forbes AA (2014) Lethal
674	interactions between parasites and prey increase niche diversity in a tropical community. Science,
675	343 , 1240-1244.
676	
677	Cruaud A, Jabbour-Zahab R, Genson G, Curaud C, Couloux A, Kjellberg F, Rasplus J-Y (2010)
678	Laying the foundations for a new classification of Agaonidae (Hymenoptera: Chalcidoidea), a
679	multilocus phylogenetic approach. <i>Cladistics</i> , 26 , 359-387.
680	
681	de Sassi C, Staniczenko PPA, Tylianakis JM (2012) Warming and nitrogen affect size structuring
682	and density dependence in a host-parasitoid food web. <i>Philosophical Transactions of the Royal</i>
683	Society B: Biological Sciences 367 3033–3041
684	
685	de Sassi C. Tylianakis JM (2012) Climate Change Disproportionately Increases Herbivore over
686	Plant or Parasitoid Biomass <i>PLoS ONE</i> 7 e40557
687	
688	Derocles SAP Plantegenest M Simon LC Taberlet P Le Ralec A (2012a) A universal method
680	for the detection and identification of Anhidiinae parasitoids within their anhid hosts. Molecular
600	Feelow Resources 12 634-645
601	Ecology Resources, 12, 054-045.
602	Derocles SAP Le Palec A Plantegenest M Chaubet B Cruaud C Cruaud A Pasplus I V (2012b)
602	Identification of molecular markers for DNA barcoding in the Anhidiinae (Hym. Braconidae)
604	Molecular Ecology Personness 12, 107, 208
694 605	Moleculur Ecology Resources, 12, 197-208.
606	Dereales SAP La Palae & Passon MM Marat M Walton & Evans DM Diantagonast M (2014)
090	Melecular analysis reveals high compartmentalization in anhid primary persited networks and
697	low peregited shoring between one and non-principal mary parasitold networks and
698	low parasitold sharing between crop and noncrop habitats. <i>Molecular Ecology</i> , 23, 3900-3911.
599	Develop SAD Dehen DA Dymhroll AI Kitzen INI Maggel E Deuvert C Dientegeneet M Veeher
700	Derocies SAP, Bonan DA, Dumoreil AJ, Kitson JJN, Massoi F, Pauvert C, Plantegenest M, vacher
701	C, Evans DM (2018) Biomonitoring for the 21st Century: Integrating Next-Generation Sequencing
/02	Into Ecological Network Analysis. Advances in Ecological Research, 58, 1-62.
703	
704	Dong Z, Hou R, Ouyang Z, Zhang R (2013) Tritrophic interaction influenced by warming and
705	tillage: A field study on winter wheat, aphids and parasitoids. Agriculture, Ecosystems &
706	<i>Environment</i> , 181 , 144-148.
707	
708	Dormann CF, Fruend J, Bluethgen N, Gruber B (2009) Indices, graphs and null models: analyzing
709	bipartite ecological networks. The Open Ecology Journal, 2, 7-24.
710	
711	Evans DM, Pocock MJO, Memmott J (2013). The robustness of a network of ecological networks.
712	<i>Ecology Letters</i> , 16 , 844-852.
713	

Evans DM, Kitson JJN, Lunt DH, Straw NA, Pocock MJO (2016) Merging DNA metabarcoding
 and ecological network analysis to understand and build resilient terrestrial ecosystems.

- 716 *Functional Ecology*, **30**, 1904-1916.
- 717
- Fahad S, Hussain S, Chauhan BS, Saud S, Wu C, Hassan S, ... Huang J (2015) Weed growth and
 crop yield loss in wheat as influenced by row spacing and weed emergence times. *Crop Protection*, **71**, 101-108.
- 721
- Fang S, Su H, Liu W, Tan K, Ren S (2013) Infrared Warming Reduced Winter Wheat Yields and
 Some Physiological Parameters, Which Were Mitigated by Irrigation and Worsened by Delayed
 Sowing. *PLoS ONE*, 8, e67518.
- 725

Folmer O, Black M, Hoeh W, Lutz R, Vrijenhoek R (1994) DNA primers for amplification of
mitochondrial cytochrome c oxidase subunit I from diverse metazoan invertebrates. *Molecular Marine Biology and Biotechnology*, 3, 294-297.

729

Gagic V, Riggi LG, Ekbom B, Malsher G, Rusch A, Bommarco R (2016) Interactive effects of
pests increase seed yield. *Ecology and Evolution*, 6, 2149-2157.

- Garcia RA, Cabeza M, Rahbek C, Araujo MB (2014) Multiple Dimensions of Climate Change and
 Their Implications for Biodiversity. *Science*, **344**, 6183.
- 735
 736 Godfray HCJ, Beddington JR, Crute IR, Haddad L, Lawrence D, Muir JF, ... Toulmin C (2010)
 737 Food Security: The Challenge of Feeding 9 Billion People. *Science*, **327**, 812-818.
- Harte J, Saleska SR, Levy C (2015) Convergent ecosystem responses to 23-year ambient and
 manipulated warming link advancing snowmelt and shrub encroachment to transient and longterm climate-soil carbon feedback. *Global Change Biology*, 21, 2349-2356.
- 742
- Hovenden MJ, Wills KE, Schoor JKV, Williams AL, Newton PCD (2008) Flowering phenology
 in a species-rich temperate grassland is sensitive to warming but not elevated CO2. *New Phytologist*, **178**, 815-822.
- 746
- Hrček J, Godfray HCJ (2015) What do molecular methods bring to host-parasitoid food webs? *Trends in Parasitology*, **31**, 30-35.
- 749
- Hudson LN, Emerson R, Jenkins GB, Layer K, Ledger ME, Pichler DE, ... Reuman DC (2013)
 Cheddar: analysis and visualisation of ecological communities in R. *Methods in Ecology and Evolution*, 4, 99-104.
- 753
- IPCC (2014). Climate Change 2014: Mitigation of Climate Change. Contribution of Working
 Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. (eds
 Edenhofer O, Pichs-Madruga R, Sokona Y, Farahani E, Kadner S, Seyboth K, Adler A, Baum I,
 Brunner S, Eickemeier P, Kriemann B, Savolainen J, Schlömer S, von Stechow C, Zwickel T,
- Minx JC). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- 759

760 761	Jeffs CT, Lewis OT (2013) Effects of climate warming on host–parasitoid interactions. <i>Ecological Entomology</i> , 38 , 209-218.
762	
763	Jordano P (2016) Sampling networks of ecological interactions. Functional Ecology 30, 1883-
764	1893.
765	
766	Kavallieratos NG, Tomanović Z, Starý P, Athanassiou CG, Sarlis GP, Petrović O, Veroniki MA
767	(2004) A survey of aphid parasitoids (Hymenoptera: Braconidae: Aphidiinae) of Southeastern
768	Europe and their aphid-plant associations. Applied Entomology and Zoology, 39 , 527-563.
769	
770	Kemp JE, Evans DM, Augustyn WJ & Ellis AG (2017) Invariant antagonistic network structure
771	despite high spatial and temporal turnover of interactions. <i>Ecography</i> , 40 , 1315-1324.
772	
773	Kimball BA (2005) Theory and performance of an infrared heater for ecosystem warming. <i>Global</i>
774	Change Biology 11 2041-2056
775	
776	Kitson JJN Hahn C Sands RJ Straw NA Evans DM Lunt DH (2018) Detecting host-parasitoid
777	interactions in an invasive Lepidopteran using nested tagging DNA metabarcoding <i>Molecular</i>
778	Ecology In press
779	20008 <i>)</i> . In proof.
780	Krzywinski M Birol I Jones S Marra M (2011) Hive Plots – Rational Approach to Visualizing
781	Networks <i>Rriefings Rightformatics</i> 13 (5) 627-644
782	10(0), 027 011.
783	Le Lann C. Lodi M. Ellers J (2014) Thermal change alters the outcome of behavioural interactions
784	between antagonistic partners <i>Ecological Entomology</i> 39 578-588
785	
786	Le Ralec A Ribule A Barragan A Outreman Y (2011) Host range limitation caused by incomplete
787	host regulation in an aphid parasitoid. <i>Journal of Insect Physiology</i> . 57 , 363-371.
788	
789	Lesk C. Rowhani P. Ramankutty N (2016) Influence of extreme weather disasters on global crop
790	production. <i>Nature</i> , 529 , 84-87.
791	
792	Liu B. Asseng S. Müller C. Ewert F. Elliott J. Lobell DB Zhu Y (2016) Similar estimates of
793	temperature impacts on global wheat yield by three independent methods <i>Nature Climate Change</i>
794	6 1130-1136
795	
796	Lobell DB Burke MB Tebaldi C Mastrandrea MD Falcon WP Navlor RL (2008) Prioritizing
797	climate change adaptation needs for food security in 2030 Science 319 607-610
798	
799	Macfadven S. Gibson R. Polaszek A. Morris R.G. Craze P.G. Planqué R. Memmott I (2009) Do
800	differences in food web structure between organic and conventional farms affect the ecosystem
800 801	service of nest control? <i>Ecology Letters</i> 17 229-238
802	Service of post control: $Declogy Declots, 12, 22)^{-2}$.
802	Macfadven S. Craze P. Polaszek A. van Achterberg K. Memmott I (2011) Parasitoid diversity
807	reduces the variability in nest control services across time on farms. <i>Proceedings of the Royal</i>
804 805	Society of London Series R. Riological sciences 778 3387-3304
000	$DOUCLY OF DOULOU, DOUCD D. DIOLOGICAL DOUCLOS, \Delta TO, JJOT JJT.$

806 807 Maron JL, Crone E (2006) Herbivory: Effects on plant abundance, distribution and population growth. Proceedings of the Royal Society of London, Series B: Biological sciences, 273, 2575-808 809 2584. 810 811 Maxmen A (2013) Crop pests: Under attack. Nature, 50, S15-S17. 812 McCann K (2007) Protecting biostructure. Nature, 446, 29-29. 813 814 Memmott J, Craze PG, Waser NM, Price MV (2007) Global warming and the disruption of plant-815 816 pollinator interactions. *Ecology Letters*, **10**, 710-717. 817 Montero-Pau J, Gomez A, Munoz J (2008) Application of an inexpensive and high-throughput 818 genomic DNA extraction method for the molecular ecology zooplanktonic diapausing eggs. 819 Limnol. Oceanography: Methods, 6, 218–222. 820 821 822 Morris RJ, Lewis OT, Godfray HCJ (2004) Experimental evidence for apparent competition in a tropical forest food web. Nature, 428, 310-313. 823 824 825 Morris RJ, Sinclair FH, Burwell CJ (2015) Food web structure changes with elevation but not rainforest stratum. Ecography, 38, 792-802. 826 827

- O'Leary GJ, Christy B, Nuttal J, Huth N, Cammarano D, Stöckle C, ... Asseng S (2015) Response
 of wheat growth, grain yield and water use to elevated CO₂ under a Free-Air CO₂ Enrichment
 (FACE) experiment and modelling in a semi-arid environment. *Global Change Biology*, 21: 26702686.
- 832

Olesen JE, Trnka M, Kersebaum KC Skjelvag AO, Seguin B, Peltonen-Sainio P, ... Micale F
(2011) Impacts and adaptation of European crop production systems to climate change. *European Journal of Agronomy*, 34, 96-112.

- 836
- Parmesan C (2006) Ecological and evolutionary responses to recent climate change. *Annual Review of Ecology, Evolution and Systematics*, **37**, 637-669.
- Peralta G, Frost CM, Rand TA, Didham RK, Tylianakis J (2014) Complementarity and redundancy
 of interactions enhance attack rates and spatial stability in host–parasitoid food webs. *Ecology*, 95, 1888-1896.
- 843
- Pocock MJO, Evans DM, Memmott J (2012) The robustness and restoration of a network of ecological networks. *Science*, **335**, 973-977.
- 846
- Price MV, Waser NM (2000) Responses of subalpine meadow vegetation to four years of
 experimental warming. *Ecological Applications*, 10, 811-823.
- 850 R Core Team (2016) R: A language and environment for statistical computing. R Foundation for
- 851 Statistical Computing, Vienna, Austria. Available from: https://www.R-project.org/.

852 853 854	Raimundo RLG, Guimarães PR, Evans DM (2018) Adaptive Networks for Restoration Ecology. <i>Trends in Ecology and Evolution</i> . In Press.
855 856 857	Rand TA, Tscharntke T (2007) Contrasting effects of natural habitat loss on generalist and specialist aphid natural enemies. <i>Oikos</i> , 116 , 1353-1362.
859 860 861	Raso L, Sint D, Mayer R, <i>et al.</i> (2014) Intraguild predation in pioneer predator communities of alpine glacier forelands. <i>Molecular Ecology</i> , 23 , 3744-3754.
862 863 864	Reeve JD, Cronin T (2010) Edge behaviour in a minute parasitic wasp. Journal of Animal Ecology, 79 , 483-490.
865 866 867	Rivera-Hutinel A, Bustamante RO, Marín VH, Medel R (2012) Effects of sampling completeness on the structure of plant-pollinator networks. <i>Ecology</i> 93 , 1593–1603.
868 869 870 871	Rollinson CR, Kaye M (2012) Experimental warming alters spring phenology of certain plant functional groups in an early successional forest community. <i>Global Change Biology</i> , 18 , 1108-1116.
872 873	Romo CM, Tylianakis JM (2013) Elevated Temperature and Drought Interact to Reduce Parasitoid Effectiveness in Suppressing Hosts. <i>PLoS ONE</i> , 8 : e58136.
875 876	Sala OE, Chapin FS, Armesto JJ, Berlow E, Bloomfield J, Dirzo R, Wall D.H. (2000) Biodiversity - Global biodiversity scenarios for the year 2100 <i>Science</i> , 287 , 1770-1774.
877 878 879	Säterberg T, Sellman S, Ebenman B (2013) High frequency of functional extinctions in ecological networks. <i>Nature</i> , 499 , 468-471.
880 881 882 883	Sherry RA, Zhou XH, Gu SL, Arnone JA, Schimel DS, Verburg PS, Luo Y (2007) Divergence of reproductive phenology under climate warming. <i>Proceedings of the National Academy of Sciences of the United States of America</i> , 104 , 198-202.
884 885 886 887	Staniczenko, PPA, Lewis, OT, Tylianakis, JM, Albrecht, M, Coudrain, V, Klein, A-M. et al. (2017) Predicting the effect of habitat modification on networks of interacting species. <i>Nature Communications</i> , 8 , 792.
889 890	Starý P (1989) Incomplete parasitization in aphids and its role in pest management. <i>Acta Entomologica Bohemoslovaca</i> , 86 , 356-367.
891 892 893	Starý P (2006) <i>Aphid Parasitoids of the Czech Republic</i> . Akademie Ved Ceske Republiky, Czech Republic.
895 896 897	Suttle KB, Thomsen MA, Power ME (2007) Species interactions reverse grassland responses to changing climate. <i>Science</i> , 315 , 640-642.

Sydes C, Miller GR (1988) Range management and nature conservation in the British Uplands. 898 899 In: Ecological Change in the Uplands (eds Usher MB, Thompson DBA, editors), pp. 323-337. Blackwell Scientific Publications, Oxford, United Kingdom. 900 901 Thompson, RM, Brose, U, Dunne, JA, Hall, RO, Hladyz, S, Kitching, RL et al. (2012). Food webs: 902 reconciling the structure and function of biodiversity. Trends in Ecology and Evolution, 27, 689-903 697. 904 905 906 Traugott M, Bell JR, Broad GR, Powell W, van Veen FJF; Vollhardt IM, Symondson WOC (2008) 907 Endoparasitism in cereal aphids: molecular analysis of a whole parasitoid community. Molecular 908 Ecology, 17, 3928-3938. 909 Traugott M, Bell JR, Raso L, Sint D Symondson WOC (2011). Generalist predators disrupt 910 parasitoid aphid control by direct and coincidental intraguild predation. Bulletin of Entomological 911 Research, 102, 239-247. 912 913 914 Tylianakis JM, Tscharntke T, Klein AM (2006) Diversity, ecosystem function, and stability of 915 parasitoid host interactions across a tropical habitat gradient. Ecology, 87, 3047-3057. 916 917 Tylianakis JM, Tscharntke T, Lewis OT (2007) Habitat modification alters the structure of tropical host-parasitoid food webs. Nature, 445, 202-205. 918 919 920 Tylianakis JM, Didham RK, Bascompte J Wardle DA (2008) Global change and species interactions in terrestrial ecosystems. Ecology Letters, 11, 1351-1363. 921 922 923 Tylianakis, JM, Laliberte, E, Nielsen, A & Bascompte, J (2010) Conservation of species interaction networks. Biological Conservation, 143, 2270-2279. 924 925 van Emden HF, Harrington R (2007). Aphids as Crop Pests. CAB International, Wallingford, 926 Oxon, United Kingdom. 927 928 929 van Veen FJF, Morris RJ, Godfray HCJ (2006) Apparent competition, quantitative food webs, and the structure of phytophagous insect communities. Annual Review of Entomology, 51, 187-208. 930 931 Wan S, Luo Y, Wallace LL (2002) Changes in microclimate induced by experimental warming 932 and clipping in tallgrass prairie. Global Change Biology, 8, 754-768. 933 934 White JW, Kimball BA, Wall GW, Ottman MJ, Hunt LA (2011) Responses of time of anthesis 935 936 and maturity to sowing dates and infrared warming in spring wheat. Field Crops Research, 124, 937 213-222 938 939 Wirta HK, Hebert PDN, Kaartinen R, Prosser SW, Varkonyi G, Roslin T (2014) Complementary molecular information changes our perception of food web structure. Proceedings of the National 940 Academy of Sciences of the United States of America, 111, 1885-1890. 941 942

- Wu Z, Dijkstra P, Koch GW, Peñuselas J, Hungate BH (2011) Responses of terrestrial ecosystems 943
- to temperature and precipitation change: a meta-analysis of experimental manipulation. Global 944 *Change Biology*, **17**, 927-942. 945

947 **Data accessibility**

- 948 DNA sequences were assigned Genbank accession numbers: MF154009 MF154409
- Plot level plant, insect and network data is available on Dryad: doi:10.5061/dryad.80vd7q6
- 950

951 Author contributions

- 952 DME designed the project. SAPD and SCFB performed the field sampling. SAPD and DHL
- 953 developed the molecular methodology. SAPD, SCFB and PCN performed the molecular work in
- the laboratory. EDM processed the crop yield data. SAPD and DME analysed the data. SAPD and
- 955 DME wrote the first draft of the manuscript, all authors contributed substantially to revisions.
- 956

957 Supporting information

- Additional supporting information may be found in the online version of this article.
- Figure S1 Experimental layout of the simulated climate change experiment at Stockbridge Technology Centre, North Yorkshire, UK.
- 961 Table S1 Qualitative network descriptors (LD, C, G, V) and unweighted quantitative network
- 962 descriptors (LD'q, C'q, G'q, V'q) for each treatment (mean ± standard deviation).

963 **Tables and figure captions**

964

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

Table 2. Weighted quantitative network descriptors (LDq, Cq, Gq) of tri-partite networks and bipartite (plant-aphid and aphid-parasitoid) networks for each treatment (mean \pm standard deviation). Vq and IEq are presented in Figure 2. Network descriptors were calculated for each of the 24 networks and then compared to each other. Effects of treatments on network descriptors were tested with GLM (Family Gaussian; F-test). W+P: warming and precipitation; \uparrow P: increase in precipitation; \uparrow T°: increase in temperature; sd: standard deviation. Significant effects at a Bonferroni-corrected α of 0.001 are in bold.

978

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 wheat plants / m^2) and crop yield (g / m^2) for each treatment (mean ± standard error). Measurements of *T. aestivum* were calculated for each of the 24 experimental plots and then compared to each other. Effects of treatments were tested with GLM (Family Gaussian; F-test; non-crop cover and pest aphid abundance were not included in these models). Significant effects (p < 0.05) are in bold.

985

986**Table 4.** Effect of treatments and covariates on the density of wheat (number of wheat plants / m^2)987and on the crop yield (g/m²). Warming treatment, precipitation treatment and non-crop cover were988included in a single GLM (Family Gaussian; F-test) when assessing their effects on wheat density.989Warming treatment, precipitation treatment and pest aphid abundance were included in a single990GLM (Family Gaussian; F-test) when assessing their effects on crop yield. Significant effects (p991< 0.05) are in bold.</td>

Table 5. Generalized linear models comparisons for the density of the wheat (number of wheat plants / m^2) and the crop yield (g/m²). AIC were calculated for GLMs including only the warming and the precipitation treatments (GLM1, models presented in Table 3) and for GLMs including warming and precipitation treatments, non-crop cover or wheat aphid abundance as covariate (GLM2, models presented in Table 4).

998

999

- 1001
- 1003

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

1008

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

1013

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







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

	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 ± 0.632	20.5 ± 4.806	77.167 ± 4.215	2.667 ± 1.033	46.167 ± 19.682	31.167 ± 7.494	0.339 ± 0.077	0.037 ± 0.038	0.082 ± 0.072	8.333 ± 2.16	12.833 ± 3.488
Precipitation	1.667 ± 0.816	19 ± 4.195	78.833 ± 1.602	2.167 ± 0.753	59.667 ± 55.479	36 ± 13.387	0.347 ± 0.111	0.042 ± 0.028	0.063 ± 0.053	7.833 ± 1.472	11.667 ± 2.066
Warming	2.667 ± 1.033	33.333 ± 16.525	62.5 ± 14.053	2.833 ± 0.753	183.333 ± 109.485	86.333 ± 49.443	0.39 ± 0.093	0.041 ± 0.014	0.067 ± 0.033	7.833 ± 1.941	13.333 ± 3.077
W+P	1.833 ± 0.753	24.5 ± 10.635	68.333 ± 10.801	2.667 ± 0.816	286.167 ± 267.655	97.167 ± 55.315	0.362 ± 0.067	0.031 ± 0.023	0.084 ± 0.044	5.5 ± 0.548	10 ± 1.265
↑P F-value	3.09	1.519	1.043	0.966			0.079	0.082	0.044	4.247	4.413
↑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
↑T° F-value	1.577	4.78	11.746	0.966			0.851	0.091	0.02	4.247	0.297
↑T° p-value	0.223	0.04	0.003	0.337	<0.001	0.009	0.367	0.766	0.889	0.052	0.592

Table 2. Weighted quantitative network descriptors (LDq, Cq, Gq) of tri-partite networks and bipartite (plant-aphid and aphidparasitoid) networks for each treatment (mean \pm standard deviation). Vq and IEq are presented in Figure 2. Network descriptors were calculated for each of the 24 networks and then compared to each other. Effects of treatments on network descriptors were tested with GLM (Family Gaussian; F-test). W+P: warming and precipitation; \uparrow P: increase in precipitation; \uparrow T°: increase in temperature; sd: standard deviation. Significant effects at a Bonferroni-corrected α of 0.001 are in bold.

	Plant-aphid-par	asitoid network	CS	Plant-aphid net	works		Aphid-parasitoi	id networks	
	LDq	Cq	Gq	LDq	Cq	Gq	LDq	Cq	Gq
	$1.945 \pm$	0.157 ±	_	$1.284 \pm$	$0.297 \pm$	1.111 ±	$3.305 \pm$	$0.317 \pm$	$1.231 \pm$
Control	0.452	0.045	1.142 ± 0.1	0.175	0.085	0.183	0.828	0.095	0.163
		$0.175 \pm$	$1.197 \pm$	$1.322 \pm$	$0.380 \pm$	$1.164 \pm$	$3.445 \pm$	$0.354 \pm$	$1.266 \pm$
Precipitation	1.978 ± 0.22	0.039	0.201	0.197	0.104	0.234	0.504	0.072	0.174
	$1.593 \pm$	$0.125 \pm$	$1.131 \pm$	$1.223 \pm$	$0.245 \pm$	$1.113 \pm$	$2.369 \pm$	$0.228 \pm$	$1.170 \pm$
Warming	0.208	0.035	0.093	0.116	0.096	0.123	0.579	0.056	0.124
Warming+Precipitatio	$1.589 \pm$	$0.162 \pm$	$1.159 \pm$		$0.306 \pm$	$1.066 \pm$	$2.307 \pm$	$0.285 \pm$	$1.361 \pm$
n	0.136	0.028	0.128	1.251 ± 0.11	0.094	0.148	0.221	0.042	0.185
↑P F-value	0.015	2.789	0.474	0.239	3.018	0.002	0.024	2.409	2.373
↑P p-value	0.905	0.11	0.499	0.63	0.097	0.966	0.878	0.136	0.138
↑T° F-value	9.168	1.859	0.161	0.944	2.284	0.37	16.985	6.724	0.053
↑T° p-value	0.006	0.187	0.693	0.342	0.146	0.549	< 0.001	0.017	0.821

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 wheat plants / m2) and crop yield (g / m2) for each treatment (mean \pm standard error). Measurements of T. aestivum were calculated for each of the 24 experimental plots and then compared to each other. Effects of treatments were tested with GLM (Family Gaussian; F-test; non-crop cover and pest aphid abundance were not included in these models). Significant effects (p < 0.05) are in bold.

	Number of seeds	Seed weight / ear (g)	Density of wheat	Yield (g/m2)
Control mean \pm se	46.67 ± 1.72	2.46 ± 0.11	534.7 ± 57.5	1323.7 ± 192.4
Precipitation mean \pm 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 \pm 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

Table 4. Effect of treatments and covariates on the density of wheat (number of wheat plants / m^2) and on the crop yield (g/m²). Warming treatment, precipitation treatment and non-crop cover were included in a single GLM (Family Gaussian; F-test) when assessing their effects on wheat density. Warming treatment, precipitation treatment and pest aphid abundance were included in a single GLM (Family Gaussian; F-test) when assessing their effects on crop yield. Significant effects (p < 0.05) are in bold.

		Density of w	heat	Crop yield (g/m ²)	
	d.f.	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

Table 5. Generalized linear models comparisons for the density of the wheat (number of wheat plants $/ m^2$) and the crop yield (g/m²). AIC were calculated for GLMs including only the warming and the precipitation treatments (GLM1, models presented in Table 3) and for GLMs including warming and precipitation treatments, non-crop cover or wheat aphid abundance as covariate (GLM2, models presented in Table 4).

	AIC GLM1: Treatments	AIC GLM2: Treatments with
	only	covariate
Density of wheat Crop yield	312.3637	272.2618
(g/m^2)	362.4188	351.2199