Eco-evolutionary feedbacks promote fluctuating selection and long-term stability of species-rich antagonistic networks

Authors: Cecilia Siliansky de Andreazzi, Paulo R. Guimarães Jr and Carlos J. Melián.

Supporting Information

Sensitivity analysis

We performed Latin Hypercube Sampling for exploring (i) higher resolution effects of the α and γ parameters on the coevolutionary dynamics and (ii) exploring the parameter space of intrinsic birth rates, phi and intraspecific competition in the four selection scenarios. In the first analysis (Figures M1) we explored a higher resolution of the α and γ scenario parameters, keeping the other parameters equal to the ones reported in Table S1. In the second analysis (Figures xxx) we explored the parameter space of intrinsic birth rates, phi and intraspecific competition, keeping the selection scenarios equal to the ones explored in the main paper. For clarity we show the results for a pair of species (one exploiter and one victim). We performed the Latin Hypercube Sampling using *R package pse*.

In the first analysis we found that, at small values, the strength of environmental selection (α) has a strong linear positive effect in abundance and negative non linear effect on trait variances. However this effect is smoother at high values of α (Figure M1). This pattern was not observed for the strength of interaction selection (γ) parameter. This indicates that when environmental selection is not so restrictive, reciprocal selection can result in greater coevolutionary changes. However, when environmental selection is strong this restricts the potential for coevolution.
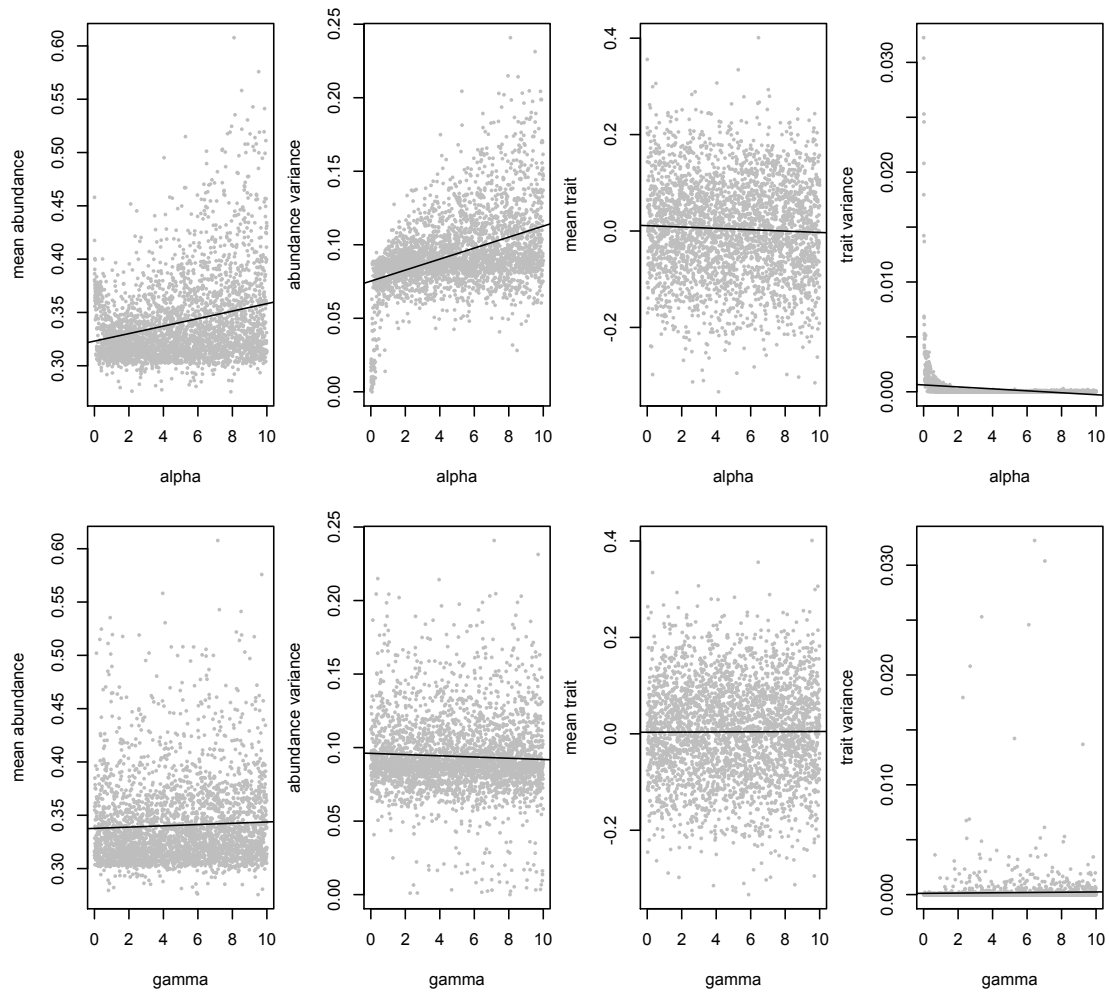
Figure M1: Effects of the strengths of environmental selection (alpha) and interaction selection (gamma) on community mean abundance, abundance variance, mean trait and trait variance.

In the second analysis, we found a strong positive effect of victim growth rate on ecological and evolutionary dynamics (mean abundance, abundance variance, mean trait, trait variance, Figures M2-M5). Exploiter growth rate had a negligible effect on eco-evolutionary dynamics. The phi parameter had a positive effect on mean abundance, negative effect on abundance variance and positive effect on trait mean and variance, in special when the interaction selection was strong. In the other scenarios the effect of phi parameter was negligible. Intraspecific competition negatively affected ecological and evolutionary dynamics. The effects of these variables were consistent in the four selection scenarios and therefore comparisons among scenarios should not be affected by interactions effects between parameters and scenario.
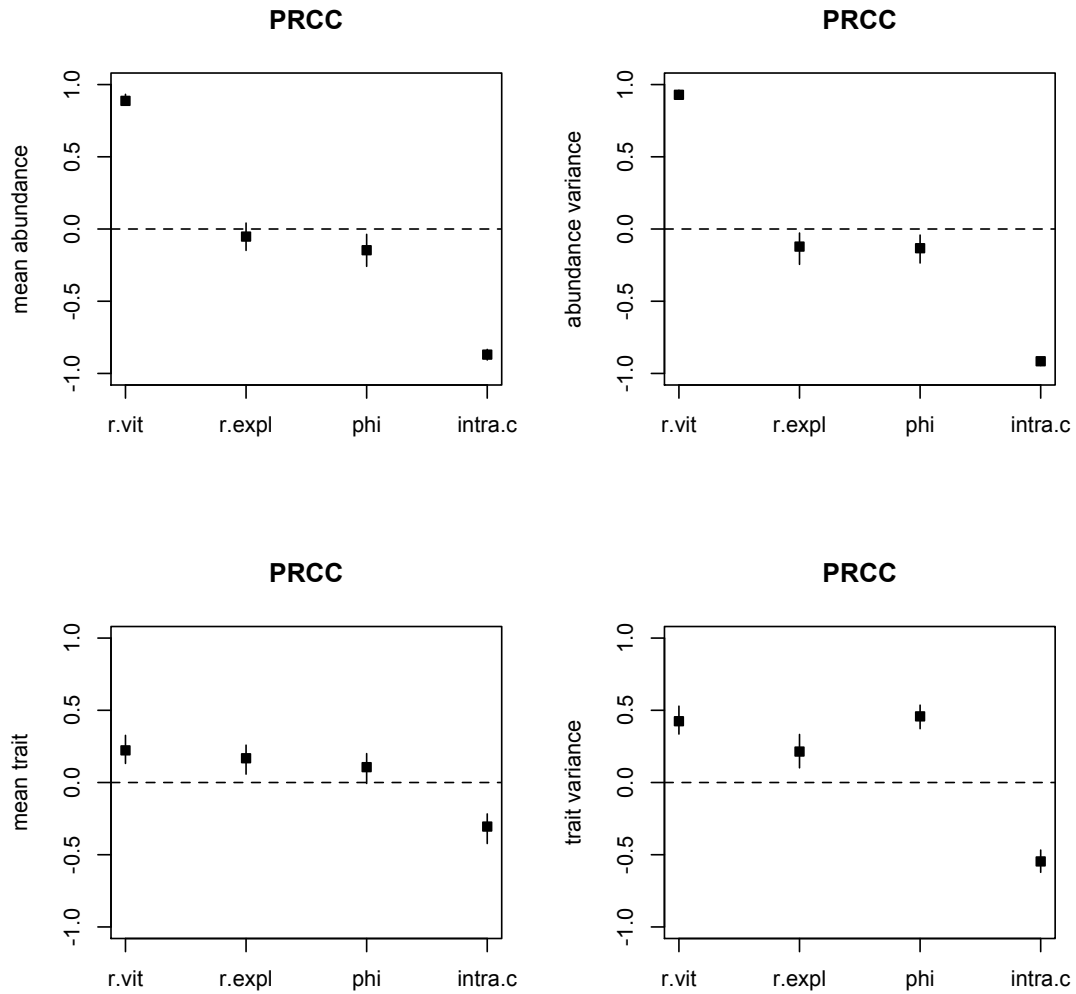
Figure M2: Partial rank correlation coefficients (PRCC) of the parameters victim intrinsic growth rate (r.vit), exploiter intrinsic growth rate (r.expl), slope of selection gradient (phi) and intraspecific competition (intra.c) for a pair of exploiter and victim species in the scenario with weak environmental and weak interaction selection. The partial rank correlation coefficient measures the strength of the linear association between the result and each input parameter after removing the linear effect of the other parameters. The confidence intervals were generated by bootstrapping.
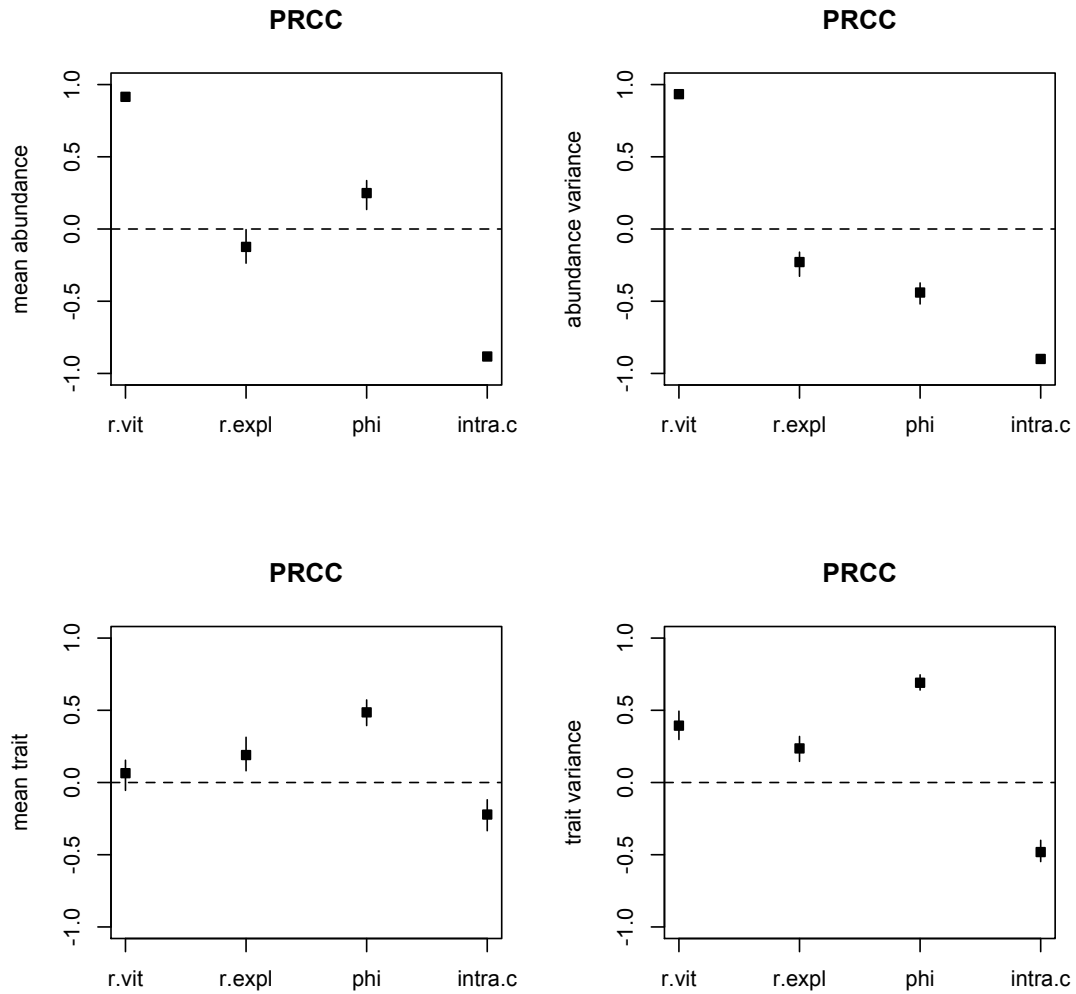
Figure M3: Partial rank correlation coefficients (PRCC) of the parameters victim intrinsic growth rate (r.vit), exploiter intrinsic growth rate (r.expl), slope of selection gradient (phi) and intraspecific competition (intra.c) for a pair of exploiter and victim species in the scenario with weak environmental and strong interaction selection. The partial rank correlation coefficient measures the strength of the linear association between the result and each input parameter after removing the linear effect of the other parameters. The confidence intervals were generated by bootstrapping.
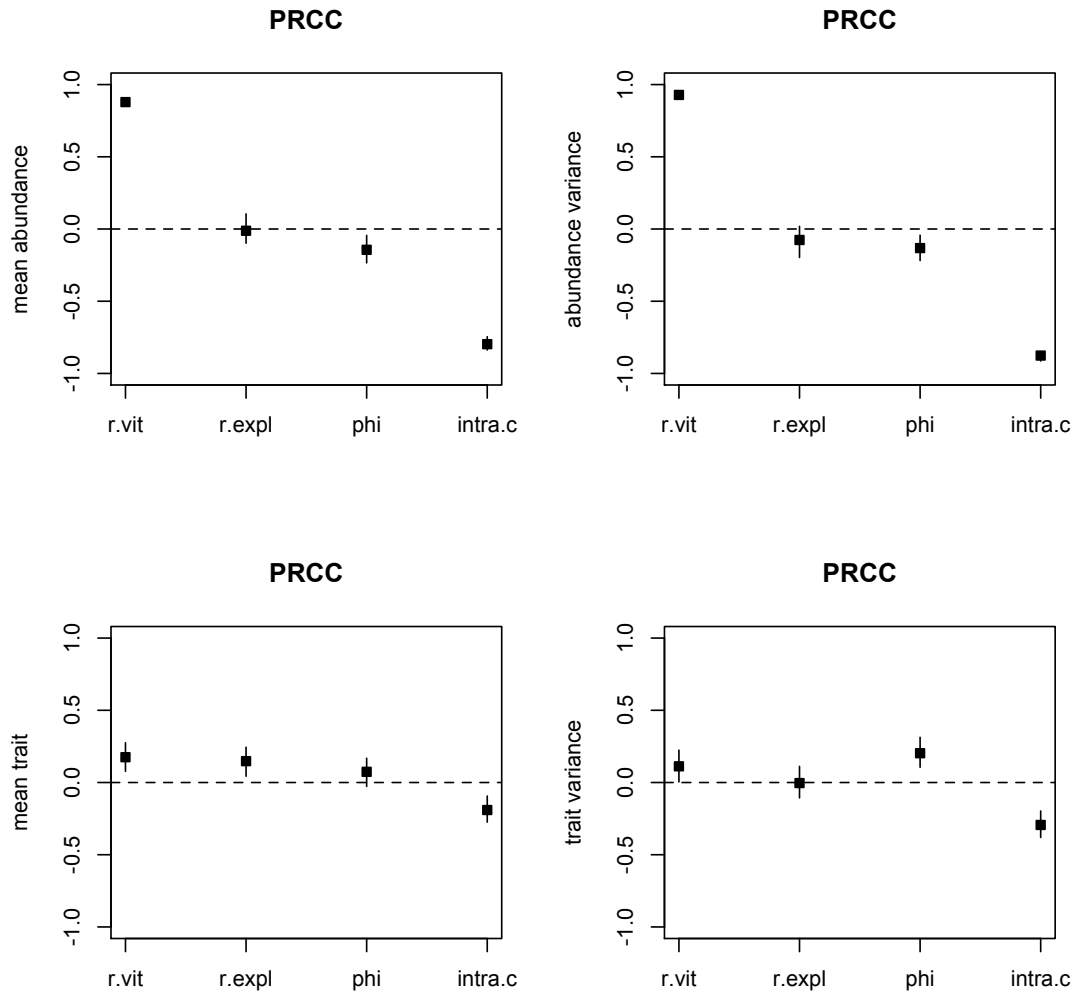
Figure M4: Partial rank correlation coefficients (PRCC) of the parameters victim intrinsic growth rate (r.vit), exploiter intrinsic growth rate (r.expl), slope of selection gradient (phi) and intraspecific competition (intra.c) for a pair of exploiter and victim species in the scenario with strong environmental and weak interaction selection. The partial rank correlation coefficient measures the strength of the linear association between the result and each input parameter after removing the linear effect of the other parameters. The confidence intervals were generated by bootstrapping.
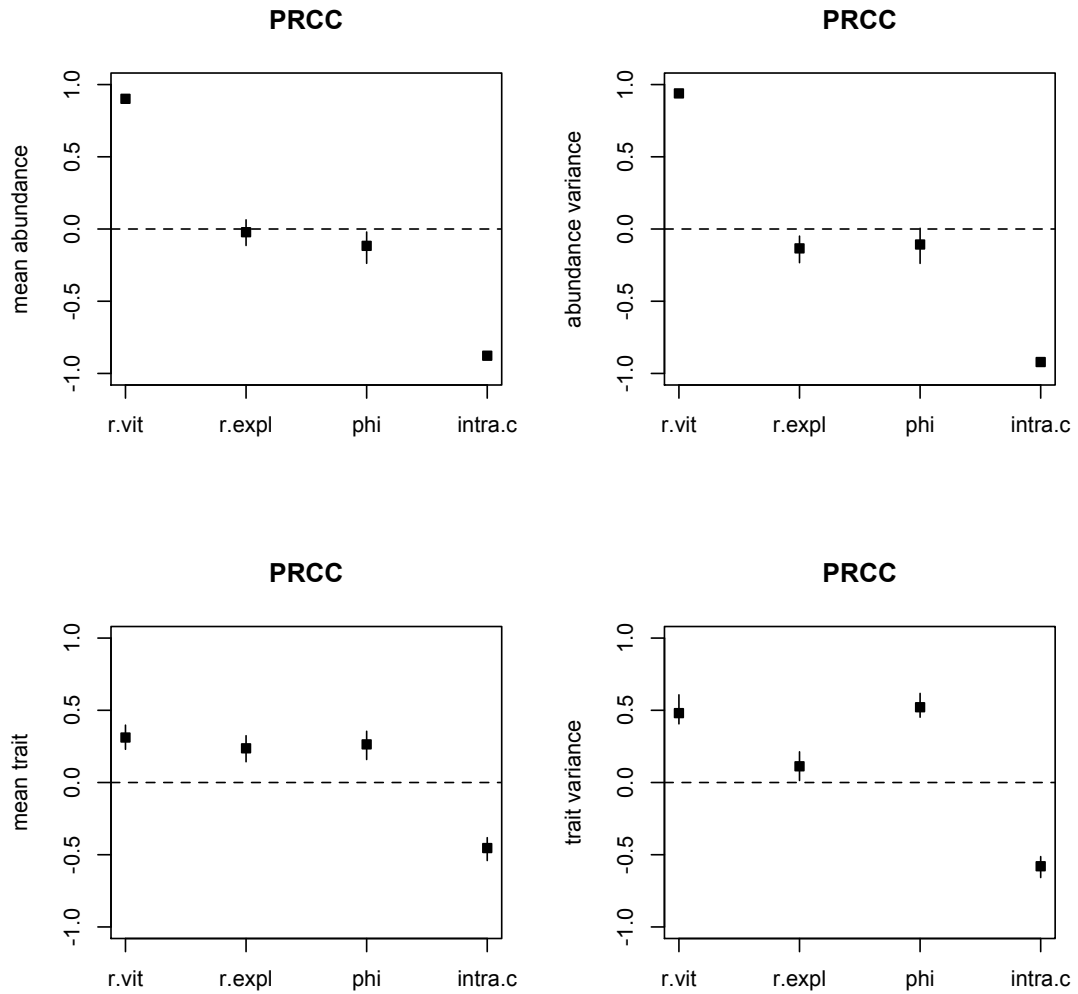
Figure M5: Partial rank correlation coefficients (PRCC) of the parameters victim intrinsic growth rate (r.vit), exploiter intrinsic growth rate (r.expl), slope of selection gradient (phi) and intraspecific competition (intra.c) for a pair of exploiter and victim species in the scenario with strong environmental and strong interaction selection. The partial rank correlation coefficient measures the strength of the linear association between the result and each input parameter after removing the linear effect of the other parameters. The confidence intervals were generated by bootstrapping.

Eco-evolutionary dynamics

Here we illustrate the eco-evolutionary dynamics in a very simple network (two victims and one exploiter community). We illustrate trait and abundance dynamics in the four scenarios, showing that when biotic interactions are more important than environmental pressures, abundances are higher, interactions are stronger, and traits are more labile.
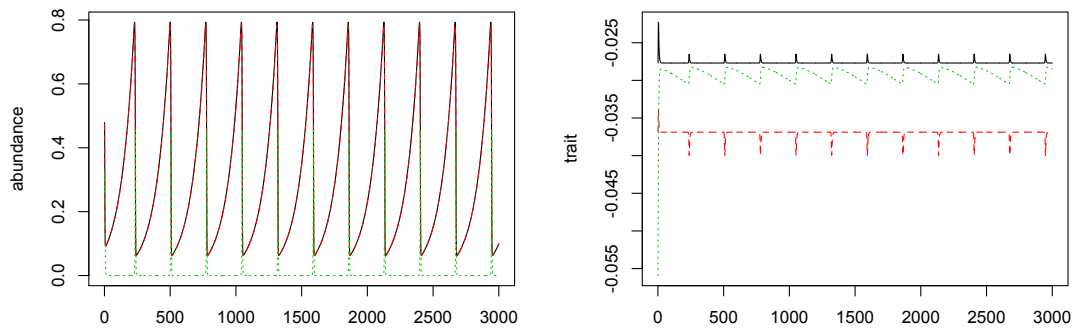

Figure M6: Abundance and trait dynamics in time for a very simple network (two victims and one exploiter community) in the scenario with weak environmental and weak interaction selection. Black and red lines are victim species and green line is the exploiter species.
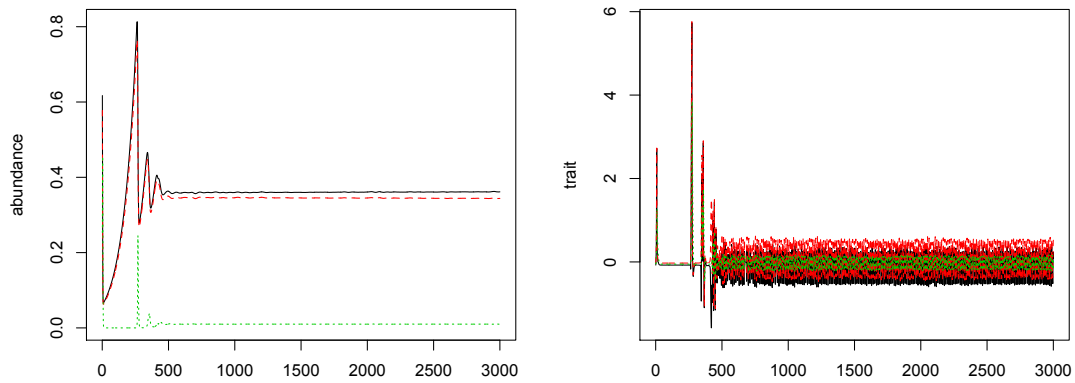
Figure M7: Abundance and trait dynamics in time for a very simple network (two victims and one exploiter community) in the scenario with weak environmental and strong interaction selection. Black and red lines are victim species and green line is the exploiter species.

Figure M8: Abundance and trait dynamics in time for a very simple network (two victims and one exploiter community) in the scenario with strong environmental and weak interaction selection. Black and red lines are victim species and green line is the exploiter species.
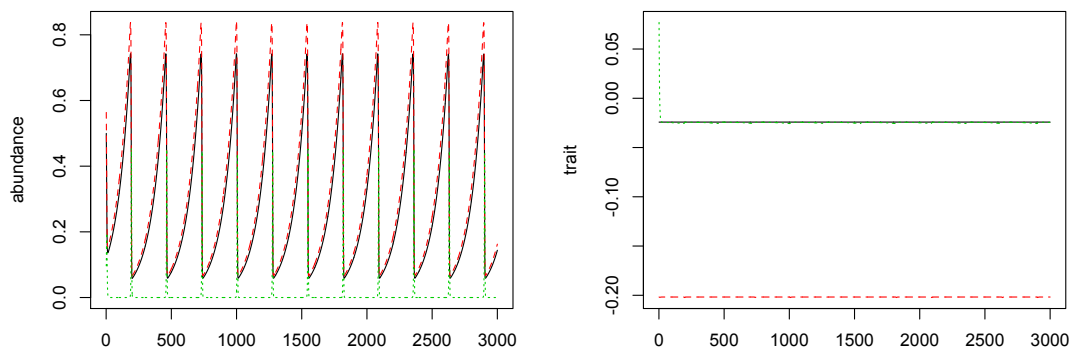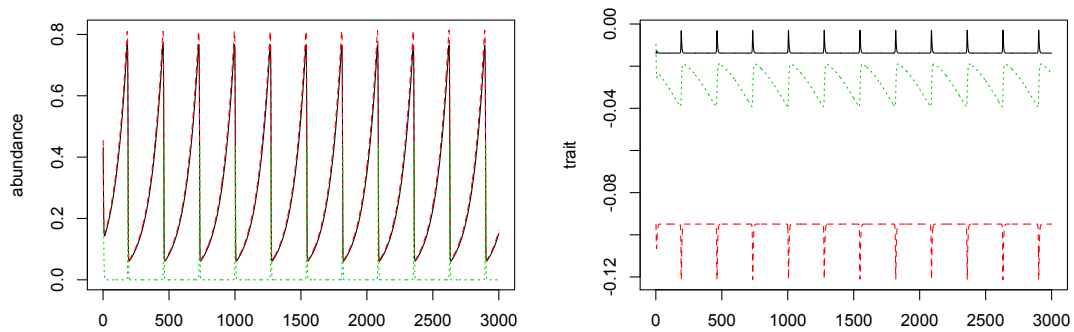
Figure M9: Abundance and trait dynamics in time for a very simple network (two victims and one exploiter community) in the scenario with strong environmental and strong interaction selection. Black and red lines are victim species and green line is the exploiter species.

Empirical antagonistic networks and network structure

Species richness range from 12 species in assemblages of bacterias and phages to 31 species in communities of fish hosts and their parasites (Table S2). To explore the effects of network structure on eco-evolutionary dynamics, we use four network descriptors: (i) species richness, (ii) connectance, *i.e.,* the proportion of realized interactions, (iii) nestedness and (iv) modularity. Nestedness is a pattern of interactions in which specialist species tend to interact with subsets of species that interact with more generalist species [1]. We use the metric NODF [2] to estimate

nestedness, computed using ANINHADO [3]. Modularity characterizes groups of species that have more interactions within groups than among groups [4]. The network degree of modularity is estimated using a simulated annealing algorithm to optimize the metric Q for bipartite networks [5], calculated using the software MODULAR [6]. These metrics are widely used in the literature because they seem to play out an important role in the coexisting number of species [7,8]

We used z-scores to compare levels of nestedness and modularity across different networks. The nestedness z-score, $N_z = \dfrac{N - \overline{N_{null}}}{\sigma_{N_{null}}}$, and modularity z-score,

$Q_z = \dfrac{Q - \overline{Q_{null}}}{\sigma_{Q_{null}}}$, measure the degree of nestedness or modularity of each empirical network in relation the mean expected nestedness and modularity under a given null model. $\overline{N_{null}}$ and $\overline{Q_{null}}$ are the average N and Q values and $\sigma_{N_{null}}$ and $\sigma_{Q_{null}}$ are their standard deviations after 1000 runs of the null model. We used null model 2 of [1], which assumes that the probability of drawing an interaction is proportional to the mean number of interactions of the exploiter and victim species. This null model was used to control the effects of heterogeneity in number of interactions, connectance and species richness on nestedness and modularity [1].

To investigate if a species degree of generalization or specialization within the network determines its abundance and trait dynamics, we characterized each species according to the two descriptors: (i) normalized degree, which is the number of interactions normalized by the maximal number of potential partners in the other trophic level [9]; and (ii) standardized Kullback-Leibler distance (d'), which is a relative entropy measure for complementary specialization and ranges from 0 for the

most generalized to 1 for the most specialized species [10].

1. Bascompte, J., Jordano, P., Melián, C. J. & Olesen, J. M. 2003 The nested assembly of plant-animal mutualistic networks. *Proc. Natl. Acad. Sci. U. S. A.* **100**, 9383–7. (doi:10.1073/pnas.1633576100)

2. Almeida-Neto, M., Guimarães, P. R., Loyola, R. D. & Ulrich, W. 2008 A consistent metric for nestedness analysis in ecological systems: reconciling concept and measurement. *Oikos* **117**, 1227–1239. (doi:10.1111/j.2008.0030-1299.16644.x)

3. Guimarães, P. R. & Guimarães, P. 2006 Improving the analyses of nestedness for large sets of matrices. *Environ. Model. Softw.* **21**, 1512–1513. (doi:10.1016/j.envsoft.2006.04.002)

4. Olesen, J. M., Bascompte, J., Dupont, Y. L. & Jordano, P. 2007 The modularity of pollination networks. *Proc. Natl. Acad. Sci. U. S. A.* **104**, 19891–6. (doi:10.1073/pnas.0706375104)

5. Barber, M. J. 2007 Modularity and community detection in bipartite networks. *Phys. Rev. E - Stat. Nonlinear, Soft Matter Phys.* **76**, 1–11. (doi:10.1103/PhysRevE.76.066102)

6. Marquitti, F. M. D., Guimarães, P. R., Pires, M. M. & Bittencourt, L. F. 2014 MODULAR: software for the autonomous computation of modularity in large network sets. *Ecography (Cop.).* **37**, 221–224. (doi:10.1111/j.1600-0587.2013.00506.x)

7.   Thébault, E. & Fontaine, C. 2010 Stability of ecological communities and the architecture of mutualistic and trophic networks. *Science* **329**, 853–6. (doi:10.1126/science.1188321)

8.   Pires, M. M. & Guimarães, P. R. 2013 Interaction intimacy organizes networks of antagonistic interactions in different ways. *J. R. Soc. Interface* **10**, 20120649. (doi:10.1098/rsif.2012.0649)

9.   Martín González, A. M., Dalsgaard, B., Olesen, J. M. & Martı, A. M. 2010 Centrality measures and the importance of generalist species in pollination networks. *Ecol. Complex.* **7**, 36–43. (doi:10.1016/j.ecocom.2009.03.008)

10. Blüthgen, N. N., Menzel, F. & Blüthgen, N. N. 2006 Measuring specialization in species interaction networks. *BMC Ecol.* **6**, 9. (doi:10.1186/1472-6785-6-9)