

Model structure conditions ecological inference in food web reconstruction

Tanya Strydom ¹; Baran Karapunar ²; Andrew P. Beckerman ¹; Alexander Dunhill ²

Abstract: Aim

Ecological networks are widely used to compare community structure, stability, and responses to disturbance across environmental gradients. However, many networks (particularly those assembled from incomplete interaction data) require model-based reconstruction. We test how alternative reconstruction frameworks condition ecological inference by quantifying their effects on network structure and disturbance dynamics.

Location

Cleveland Basin, United Kingdom.

Time period

Toarcian extinction event (Early Jurassic, late Pliensbachian–late Toarcian, ~183 Ma).

Major taxa studied

Marine animal communities.

Methods

We reconstructed four successive communities from an identical species pool using six contrasting food-web models spanning feasible (trait-based), realised (allometric and energetic), and structural (topological) network representations. For each community and model, 100 replicate networks were generated. We quantified macro-, meso-, and micro-scale network properties and assessed differences among models using multivariate analyses. Pairwise interaction turnover was measured using link-based beta diversity. We then simulated species loss under multiple disturbance scenarios, allowing cascading extinctions, and compared predicted community states using mean absolute differences and rank concordance metrics between models.

Results

Reconstruction framework strongly influenced inferred network topology (MANOVA, $p < 0.001$), generating distinct structural signatures independent of species composition. Models that were similar in global metrics often diverged in species-level interactions, with high -turnover among inferred link sets. During disturbance simulations, species-level vulnerability rankings were broadly consistent across models, but interaction-level outcomes and cascade dynamics varied substantially. Concordance in extinction-scenario rankings was scale dependent, with higher agreement at the species level than at the interaction level.

Main conclusions

Network reconstruction functions as a structural prior that conditions ecological inference. While some aggregate patterns are robust across modelling frameworks, detailed interaction-level dynamics are highly model contingent. Comparative network studies across spatial or environmental gradients should therefore align reconstruction framework with inferential goals and explicitly evaluate sensitivity to modelling assumptions.

Keywords: Ecological networks, Biotic interactions, Community assembly, Environmental gradients, Interaction turnover, Trophic organisation, Ecosystem resilience, Macroecology

¹ 1 Introduction

² Understanding how biodiversity is organised across space and time is a central goal of macroecology and
³ biogeography. While early efforts focused primarily on species richness and composition, there is growing
⁴ recognition that ecological communities are structured not only by which species occur, but by how they
⁵ interact (Thuiller et al., 2024). Interaction networks are increasingly treated as macroecological state variables
⁶ where they are used to compare community organisation across environmental gradients, to quantify -diversity
⁷ in interaction structure, to evaluate stability-complexity relationships, and to infer vulnerability under global
⁸ change (Carstensen et al., 2014; Gravel et al., 2019; Poisot et al., 2015; Trøjelsgaard & Olesen, 2016; Tylianakis
⁹ & Morris, 2017).

¹⁰ As a result, ecological networks now play a central role in comparative analyses spanning latitudinal gradients,
¹¹ disturbance regimes, and deep-time environmental transitions (Dunhill et al., 2024; Hao et al., 2025; Michalska-
¹² Smith & Allesina, 2019; Poisot & Gravel, 2014; Roopnarine, 2006). Implicit in this expansion is the critical
¹³ assumption that network properties estimated across systems are structurally comparable, and that differences
¹⁴ among them reflect ecological signal rather than methodological artefact (Fründ et al., 2016; Jordano, 2016).

¹⁵ Yet most ecological networks are not fully observed as interaction data are incomplete and sampling is
¹⁶ uneven across historical and biogeographic contexts, across both contemporary and deep-time (Catchen et
¹⁷ al., 2023; Poisot et al., 2021; Sandra et al., 2025). Interactions must often be inferred indirectly from traits,
¹⁸ phylogeny, body size, co-occurrence, or theoretical constraints (Morales-Castilla et al., 2015; Strydom et
¹⁹ al., 2021). Network construction therefore constitutes a model-based inference step rather than a purely
²⁰ descriptive exercise. Different reconstruction frameworks encode distinct ecological assumptions about how
²¹ interactions arise - whether as biologically feasible combinations of traits, energetically optimised realised diets,
²² or topological structures constrained by macroecological regularities. These assumptions act as structural
²³ priors over network architecture (Gauzens et al., 2025; Guimarães, 2020; Petchey et al., 2011; Strydom et
²⁴ al., 2026). If alternative reconstruction models systematically generate different trophic configurations, then
²⁵ comparative analyses risk conflating ecological differences among communities with artefacts introduced by
²⁶ modelling choice. The reliability of macroecological inference therefore depends not only on ecological data,
²⁷ but on the structural assumptions embedded in network reconstruction.

²⁸ Despite rapid methodological development in interaction inference, few studies have directly evaluated how
²⁹ alternative reconstruction frameworks condition macroecological conclusions when applied to the same species
³⁰ pool. This gap is particularly consequential for comparative research, where network metrics are routinely
³¹ interpreted as indicators of environmental filtering, disturbance intensity, evolutionary history, or community

32 stability (Allesina & Tang, 2012; Delmas et al., 2018; Poisot et al., 2015). If reconstruction models encode
33 distinct structural priors over interaction topology, then differences among communities may reflect modelling
34 assumptions rather than ecological processes. We therefore test whether macroecological inference derived from
35 ecological networks is robust to variation in reconstruction framework, asking which aspects of network-based
36 inference are stable across plausible representations of interaction structure and which are intrinsically model
37 dependent.

38 Deep-time ecosystems provide an especially stringent test of this issue because interactions are not observed
39 directly and must be reconstructed explicitly (Dunhill et al., 2024; Dunne et al., 2008; Dunne et al., 2014;
40 Roopnarine, 2006), rendering modelling assumptions transparent. Against this stringency, here we re-evaluate
41 inferences made by Dunhill et al. (2024) on community structure and extinction dynamics during the early
42 Toarcian extinction event (~183 Ma), a volcanic-driven hyperthermal and marine crisis in the Early Jurassic
43 (Kemp et al., 2024). Crucially, this re-evaluation allows us to test a pivotal but often overlooked possibility -
44 that the ecological narratives regarding community stability or collapse might be as much a product of the
45 specific reconstruction method chosen as they are of the fossil data itself. By applying alternative models,
46 we can determine if Dunhill et al. (2024) conclusions remain robust or if a different choice of reconstruction
47 method would have led to fundamentally different inferences about extinction dynamics. Using four successive
48 communities drawn from an identical taxon pool, we reconstruct ecological networks under six contrasting
49 model classes spanning feasible, realised, and structural representations. For each reconstruction framework,
50 we quantify emergent topology across scales, measure interaction turnover, and simulate disturbance-driven
51 collapse. By holding species composition constant while varying the food web model used, this design isolates
52 the influence of model constrained structure on inferred food web organisation and extinction dynamics,
53 allowing us to distinguish ecological signals that are robust from those that are reconstruction contingent.

54 2 Methods

55 2.1 Study system and fossil data

56 We used fossil occurrence data from the Cleveland Basin spanning the upper Pliensbachian to the upper
57 Toarcian. This interval encompasses a major volcanic-driven hyperthermal and marine extinction event. To
58 capture network dynamics across this transition, we defined four successive paleo-communities: Pre-extinction
59 (Pliensbachian), Post-extinction (Lower Toarcian), Early recovery, and Late recovery (Middle/Upper Toarcian).
60 Each taxon was characterized using their size and Bambach's ecospace framework (Bambach et al., 2007),
61 coding for tiering, motility, and feeding mode as per Dunhill et al. (2024). Each assemblage was treated

as a community of potentially interacting taxa. The dataset includes 57 taxa across diverse groups (*e.g.*, cephalopods, bivalves, and gastropods). By restricting our analysis to a single basin with consistent lithofacies, we controlled for biogeographic noise, ensuring that structural shifts across the four time-bins reflect localised ecological responses to environmental stress rather than sampling or facies bias.

2.2 Network reconstruction approaches

2.2.1 Conceptual classification of network types

Most paleo-specific research (*e.g.*, Fricke et al. (2022); Roopnarine (2006); Shaw et al. (2024)) currently uses models from within the feasibility space. That is, the model reconstructions identify and encode the entire feasible diet of a species to build the network. These methods, however, represent only a subset of the broader spectrum of network construction approaches. Here, we present a suite of methods (Table 1) that enable the construction of a wider range of ecological networks and the exploration of a broader set of ecological questions, provided that their underlying assumptions are compatible with the constraints of fossil data. The methods include a) structural models that create species agnostic networks that are structurally ‘correct’ by assigning links between nodes based on assumptions of link distributions; and b) realised models that create networks where links between species are constrained based on some form of ‘species choice’ *e.g.*, maximising energy gain.

Table 1: Six different models that can be used to construct food webs for both this specific community but are also broadly suited to paleo network prediction. These models span all facets of the network representation space (feasibility, realised, and structural network) and are suitable for an array of different paleo communities as the data requirements fall within the limitations set by the fossil record.

Model	Assumptions	Data needs	Limitation	Network type	Key reference	Usage examples
Random	Links assigned randomly	Species richness, number of links	Parameter assumptions, species agnostic	Structural	Erdős & Rényi (1959)	Null-model comparisons; testing whether observed network structure (connectance, motifs) deviates from random expectations
Niche	Species ordered along a ‘niche axis’; interactions interval-constrained	Species richness, connectance	Parameter assumptions, species agnostic	Structural	Williams & Martinez (2008)	Evaluating trophic hierarchy and motif structure; baseline structural predictions
Allometric diet breadth model (ADBM)	Energy-maximizing predator diets	Body mass, abundance/dance/biomass	Assumes optimal foraging; does not account for forbidden links	Realised	Petchey et al. (2008)	Predicting realized predator diets; exploring secondary extinctions

Model	Assumptions	Data needs	Limitation	Network type	Key reference	Usage examples
Allometric trophic network (ATN)	Links constrained by body-size ratios and functional response	Body mass, number of basal species	Assumes only mechanico/energetic constraints	Realised	Brose et al. (2006); Gauzens et al. (2023)	Simulating species loss; evaluating network collapse dynamics
Paleo food web inference model (PFIM)	Interactions inferred using trait-based mechanistic rules	Feeding traits	Assumes feeding mechanisms; trait resolution required	Feasibility	Shaw et al. (2024)	Mapping feasible trophic interactions; assessing secondary extinctions
Body-size ratio model	Probabilistic assignment of links based on predator-prey size ratios	Body mass	Does not account for forbidden links	Realised	Rohr et al. (2010)	Estimating likely interactions; simulating cascading effects.

78 The three body mass-based models (ADBM, ATN, Body-size ratio) differ primarily in their underlying
 79 ecological assumptions. Although all three models use body mass to infer food web structure, they differ in
 80 their ecological assumptions. The ADBM is based on energy maximization under optimal foraging theory,
 81 the ATN constrains interactions via mechanically optimal consumer-resource size ratios, and the Body-size
 82 ratio model defines links probabilistically within a fixed allometric niche. Together, these approaches span
 83 bioenergetic, mechanical, and statistical interpretations of size-structured interactions.

84 **2.2.2 Network generation and replication**

85 We evaluated six models spanning this space Table 1: random and niche models (structural networks);
86 allometric diet breadth (ADBM), allometric trophic network (ATN), and Body-size ratio models (realised
87 networks); and a paleo food web inference model (PFIM; feasibility network). Expanded descriptions of
88 model assumptions, parameterisation, and link-generation rules are provided in Supplementary Material
89 S1. For each community, 100 networks were generated per model per successive community ($n = 2400$) to
90 capture stochastic variation in link assignment. Where models required species body mass or trait values,
91 these were sampled within biologically reasonable ranges to preserve relative differences among species. We
92 adopted uniform sampling by default, as alternative distributions (lognormal, truncated lognormal) have
93 negligible impact on topology (Supplementary Material S2; Figure S1). Structural models were parameterized
94 using connectance values drawn from an empirically realistic range (0.07 – 0.34), with species richness held
95 constant. Identical parameter draws were applied across comparable models within each replicate to ensure
96 comparability. For the Body-size ratio model, we followed the approach of Yeakel et al. (2014) and excluded
97 latent trait terms as opposed fitting the full model, which introduces additional inference and assumptions.

98 **2.3 Network metrics and structural analyses**

99 We quantified network structure using a suite of macro-, meso-, and micro-scale metrics Table 2, capturing
100 global properties, motif structure, and species-level variability. Differences among reconstruction approaches
101 were assessed using a multivariate analysis of variance (MANOVA), with model identity as a fixed factor
102 and the full set of network metrics as response variables. Pairwise interaction turnover was quantified using
103 link-based -diversity following the framework of Poisot et al. (2012). For each pair of reconstructed networks,
104 we represented trophic interactions as binary adjacency matrices and calculated their dissimilarity. Specifically
105 we looked at interaction rewiring among shared species (β_{OS}), which allows separation of differences arising
106 from altered interaction identities among species common to both networks. All calculations were performed
107 for all model combinations within the same community (time bin).

Table 2: Network properties used for analysis.

Metric	Definition	Scale	Reference (for maths), can make footnotes probs
Richness	Number of nodes in the network	Macro	

Metric	Definition	Scale	Reference (for maths), can make footnotes probs
Links	Normalized standard deviation of links (number of consumers plus resources per taxon)	Micro	
Connectance	L/S^2 , where S is the number of species and L the number of links	Macro	
Max trophic level	Prey-weighted trophic level averaged across taxa	Macro	Williams & Martinez (2004)
S1	Number of linear chains, normalised	Meso	Milo et al. (2002); Stouffer et al. (2007)
S2	Number of omnivory motifs, normalised	Meso	Milo et al. (2002); Stouffer et al. (2007)
S4	Number of apparent competition motifs, normalised	Meso	Milo et al. (2002); Stouffer et al. (2007)
S5	Number of direct competition motifs, normalised	Meso	Milo et al. (2002); Stouffer et al. (2007)
Generality	Normalized standard deviation of generality of a species, standardised by L/S	Micro	Williams & Martinez (2000)
Vulnerability	Normalized standard deviation of vulnerability of a species, standardised by L/S	Micro	Williams & Martinez (2000)

108 **2.4 Extinction simulations and model evaluation**

109 Following Dunhill et al. (2024), we simulated species loss from Pre-extinction networks under trait-based,
110 network-position-based, and random removal scenarios. Species were deleted sequentially, with cascading
111 secondary extinctions allowed to propagate. Simulated post-extinction states were compared to ‘observed’
112 networks using mean absolute differences (MAD) of food-web metrics Table 2 and modified true skill statistics
113 (TSS) calculated separately at the node level (species presence/absence) and link level (presence/absence of
114 interactions between species pairs). Scenarios were ranked within each reconstruction framework based on
115 MAD and TSS performance, and Kendall’s rank correlation coefficient () was used to quantify concordance
116 in scenario ordering across models. Full methodological details are provided in the Supplementary Materials.

117 **2.5 Software and Reproducibility**

118 Ecological network reconstruction and extraction of structural metrics were conducted in Julia v1.11.4
119 (Bezanson et al., 2017). All statistical analyses, model fitting (MANOVA, PERMANOVA, GAMs), and figure
120 production were performed in R v4.5.2 (R Core Team, 2024). The empirical data, derived network datasets
121 and code implementing network reconstruction, extinction simulations, and all analytical workflows is archived
122 at [Zenodo DOI].

123 **3 Results**

124 Results show that reconstruction approaches that appear similar when evaluated using global network metrics
125 can yield fundamentally different ecological narratives when interrogated at the level of interactions and
126 extinction dynamics. Across six network reconstruction approaches, inferred food web structure, species
127 interactions, and extinction dynamics differed consistently. Multivariate analyses showed pronounced separation
128 among models in network metric space. Reconstruction approach explained most of the variance in structural
129 properties, leaving a distinct signature independent of community composition. Notably, agreement among
130 models depended on the scale at which the comparison was made- approaches that were statistically similar in
131 multivariate structural space (scale 1) often diverged in inferred interactions (scale 2) or extinction dynamics
132 (scale 3). This demonstrates that structural similarity does not guarantee concordance in species-level diets or
133 trophic roles.

134 Model choice substantially influenced inferred extinction dynamics. Temporal trajectories of network collapse,
135 interaction loss, and motif reorganization differed among approaches. Although species-level extinction
136 rankings were often broadly consistent, link-level outcomes and extinction inferences were highly sensitive

¹³⁷ to reconstruction assumptions. Together, these results show that ecological inferences drawn from networks
¹³⁸ depend critically on the reconstruction framework employed.

¹³⁹ **3.1 Network structure differs among reconstruction approaches**

¹⁴⁰ Across six reconstruction approaches, network structure (network properties listed in Table 2) differed
¹⁴¹ significantly (MANOVA, Pillai's trace = 3.84, approximate $F_{40,11955} = 987.35$, $p < 0.001$), indicating that
¹⁴² model choice systematically alters inferred food web topology. Canonical discriminant analysis identified two
¹⁴³ dominant axes of variation, explaining 86% of between-model variance. LD1 correlated with vulnerability,
¹⁴⁴ direct competition motifs, and connectance. LD2 correlated with maximum trophic level and apparent
¹⁴⁵ competition motifs, reflecting vertical trophic structure (Figure 1; Table S1, Figure S1). All higher-order
¹⁴⁶ canonical variates each explained less than 9% of the remaining variance.

¹⁴⁷ [Figure 1 about here.]

¹⁴⁸ **3.1.1 Variance partitioning of network structure**

¹⁴⁹ Permutational multivariate analysis of variance revealed that reconstruction framework accounted for the
¹⁵⁰ majority of variation in multivariate network structure ($R^2 = 0.795$, $p < 0.001$), whereas temporal turnover
¹⁵¹ across extinction phases explained a comparatively small proportion of variance ($R^2 = 0.064$, $p < 0.001$).
¹⁵² The model \times time interaction contributed a further 7.1% of variance ($R^2 = 0.071$, $p < 0.001$), indicating
¹⁵³ limited but significant time-dependent divergence among reconstruction frameworks. Thus, differences among
¹⁵⁴ modelling approaches were more than an order of magnitude greater than structural differences associated
¹⁵⁵ with ecological turnover through the extinction sequence, even if the Toarcian dataset was characterized with
¹⁵⁶ a significant community turnover.

¹⁵⁷ To determine whether the dominance of the reconstruction framework reflected absolute mean shifts among
¹⁵⁸ time bins, we repeated the analysis after centring network metrics within each extinction phase. This procedure
¹⁵⁹ removes between-phase differences while retaining within-phase structural variation. Even after temporal
¹⁶⁰ bin-standardised centring, the reconstruction framework explained 84.8% of multivariate variance ($R^2 = 0.848$,
¹⁶¹ $p < 0.001$). These results demonstrate that the influence of model choice is not driven by temporal mean
¹⁶² differences, but reflects intrinsic divergence among reconstruction frameworks in how ecological interactions
¹⁶³ are organised.

164 **3.1.2 Inferred pairwise interactions vary widely among models**

165 Despite some models showing similar global metrics, specific pairwise interactions often differed. Pairwise
166 turnover revealed that certain model pairs shared very few links Figure 2. Size-based models (ADBM,
167 ATN) were broadly similar due to shared sole reliance on body-size constraints, whereas the Body-size ratio
168 model exhibited consistently higher differences to other models. PFIM showed intermediate overlap with
169 theoretical models. These results demonstrate that agreement in global network structure does not guarantee
170 concordance in species-level interactions.

171 [Figure 2 about here.]

172 **3.2 Model choice influences inferred extinction dynamics**

173 To quantify how network structure changed over time during extinction simulations and whether these
174 dynamics differed among reconstruction models, we fit generalized additive models (GAMs) to time series
175 of network-level metrics. GAMs capture non-linear temporal trajectories, allowing formal tests of whether
176 the shape of these trajectories differs among models. These model-specific temporal trajectories are shown
177 in Figure 3. For all metrics examined, the inclusion of model-specific smooth terms significantly improved
178 model fit (ANOVA model comparison: $p < 0.001$ for all metrics). Model-specific smooths differed not only
179 in magnitude but also in the timing and abruptness of change, indicating distinct modes of collapse across
180 reconstruction approaches (Tables S3–S4). Deterministic, data-driven approaches (PFIM) and allometric
181 models (ADBM, ATN) exhibited highly non-linear trajectories, showing structural shifts in connectivity
182 and motif frequency. In contrast, the Niche model produced the most consistent and gradual trajectories,
183 effectively smoothing the perceived magnitude of structural change during community collapse. These results
184 demonstrate that inferred pathways of collapse, trophic bottlenecks, and secondary extinctions are highly
185 sensitive to model choice. Corresponding raw temporal trajectories are shown in Figure S2.

186 [Figure 3 about here.]

187 To evaluate how model choice affects inferred extinction dynamics, we compared simulated post-extinction
188 networks to observed networks using mean absolute differences (MAD) for network-level metrics and true
189 skills statistics (TSS) for node- and link-level outcomes Figure 4. Across models, MAD-based rankings were
190 generally positively correlated (Kendall's $\tau = 0.13$ across structural metrics), indicating broad agreement on
191 the relative importance of extinction drivers despite substantial differences in reconstructed network structure.
192 However, agreement within the allometric models differed from patterns observed for reconstructed network
193 structure.

¹⁹⁴ Node-level TSS rankings were similarly consistent across models ($\tau = 0.26\text{--}0.90$), reflecting broadly comparable
¹⁹⁵ species removal sequences. In contrast, link-level outcomes were far more variable ($\tau = -0.48\text{--}0.29$), highlighting
¹⁹⁶ that inferences about which interactions are lost, retained, or re-established during collapse and recovery are
¹⁹⁷ highly model contingent. Together, these results suggest that while alternative models converge on similar
¹⁹⁸ species-level extinction patterns, the inferred pathways of interaction loss and cascading dynamics depend
¹⁹⁹ strongly on both reconstruction approaches.

²⁰⁰ [Figure 4 about here.]

²⁰¹ 4 Discussion

²⁰² 4.1 Network reconstruction is not neutral: structural priors shape ecological ²⁰³ theory

²⁰⁴ Food web ecology has long treated network reconstruction as a technical step preceding ecological analysis.
²⁰⁵ Once a network is assembled (whether from observation, inference, or simulation) its properties are typically
²⁰⁶ analysed as reflections of underlying ecological organisation. Implicit in this workflow is a powerful assumption
²⁰⁷ - that reconstructed networks provide structurally comparable representations of ecological communities, such
²⁰⁸ that differences in connectance, trophic structure, motif composition, or robustness primarily reflect biological
²⁰⁹ variation.

²¹⁰ This assumption is particularly critical to evaluate within the context of deep-time paleoecological data. Because
²¹¹ interactions in fossil ecosystems are never observed directly, they must explicitly be reconstructed through some
²¹² form of reconstruction approach. This necessity renders the underlying assumptions transparent but also makes
²¹³ the resulting ecological narratives highly susceptible to the constraints inherent in the chosen reconstruction
²¹⁴ framework. In these settings the risk is not just incomplete data, but the potential for methodological artefacts
²¹⁵ to be misinterpreted as genuine macroevolutionary or paleoecological signals. Consequently, deep-time studies
²¹⁶ offer a unique and stringent testing ground for determining whether community-level responses (such as
²¹⁷ stability or collapse during mass extinctions) are robust features of the ecosystem or merely byproducts of
²¹⁸ how we choose to construct the links between species.

²¹⁹ Our results challenge this assumption and reveal strong sensitivity of inference about secondary extinction
²²⁰ dynamics in paleo-foodwebs. Across an identical species pool, reconstruction frameworks explained the majority
²²¹ of variance among reconstructed network topologies, generating distinct structural signatures independent
²²² of community composition. Although some model classes converged on similar global metrics, pairwise

223 interaction turnover revealed substantial divergence in inferred trophic links. Structural similarity at the
224 level of connectance or trophic height therefore does not guarantee concordance in species roles or interaction
225 architecture.

226 Reconstruction framework explained the majority of variance in inferred food web topology, far outweighing
227 the influence of temporal turnover across extinction phases. These patterns demonstrate that the divergence
228 among reconstruction approaches reflects intrinsic differences in how models organise interactions, not temporal
229 shifts in network structure. In other words, different reconstruction approaches impose distinct structural
230 priors on inference of ecological organisation. These priors are not subtle - they propagate into emergent
231 topology, species roles, and dynamical predictions. Network structure is therefore not solely a property
232 of ecological communities; it is jointly determined by ecological data, modelling assumptions, and level of
233 organisation (Gauzens et al., 2025; Guimarães, 2020; Pichler & Hartig, 2023; Strydom et al., 2021; Strydom
234 et al., 2026).

235 This has direct implications for the interpretation of comparative network studies. Feasible, realised, and
236 structural models encode different assumptions about constraint, optimisation, and topology, and these
237 assumptions propagate into emergent metrics and dynamical predictions (Allesina & Tang, 2012; Dunne et
238 al., 2002; Michalska-Smith & Allesina, 2019; Poisot & Gravel, 2014; Solé & Montoya, 2001). When networks
239 reconstructed under different model classes are compared across spatial gradients, disturbance regimes, or
240 evolutionary transitions, part of the observed variation may derive from structural priors rather than ecological
241 process. Without explicit standardisation or sensitivity analysis, methodological heterogeneity can be mistaken
242 for biological signal. Food web ecology has devoted substantial effort to understanding how topology shapes
243 dynamics; comparatively less attention has been paid to how reconstruction method shapes topology. Our
244 findings indicate that these two questions cannot be separated.

245 4.2 Scale-dependent robustness in network-based inference

246 Importantly, reconstruction sensitivity was not uniform across network scales (macro-, meso-, micro- level
247 properties). Species-level extinction rankings were broadly consistent among model classes, whereas interaction-
248 level outcomes and cascade trajectories were highly contingent on reconstruction approach. The predominance
249 of reconstruction framework over temporal turnover (~80% vs. 6% variance explained) illustrates why coarse-
250 grained patterns like species-level extinction rankings are more robust. Model-imposed structure dominates
251 the overall topology, leaving interaction dynamics highly contingent on framework choice. This asymmetry
252 reveals a context-dependent pattern of robustness. Coarse-grained macroecological patterns (such as the
253 vulnerability of a community to collapse) can emerge from multiple plausible interaction architectures. By

254 contrast, fine-grained inferences about which links are lost, retained, or reorganised depend strongly on how
255 interactions are inferred.

256 This distinction challenges a central ambition of food web ecology: the use of detailed interaction structure to
257 diagnose mechanisms of stability and collapse. Our findings suggest that while coarse-grained patterns might
258 be shared across methods, fine-grained mechanistic narratives (such as the specific pathways of interaction
259 loss) are much more precarious. This implies that had Dunhill et al. (2024) selected a different reconstruction
260 method, the resulting inferences regarding the drivers of extinctions could have pointed to entirely different
261 ecological mechanisms. If interaction-level cascade pathways vary substantially across equally plausible
262 reconstructions, then mechanistic narratives derived from a single inferred topology may overstate their
263 precision (Allesina & Tang, 2012; Curtsdotter et al., 2011; Dunne et al., 2002). The apparent determinism of
264 extinction cascades may therefore partly reflect model-imposed structure rather than ecological inevitability.

265 For macroecology, this metric dependence clarifies where network-based inference is accurate. Aggregate
266 properties may be comparatively robust to reconstruction assumptions, whereas conclusions about interaction
267 turnover, motif reorganisation, or fine-scale trophic dynamics are intrinsically uncertain. Recognising this
268 asymmetry is essential if network analyses are to inform comparative synthesis across space and time.

269 Taken together, these results underscore that network reconstruction is not a neutral preprocessing step but
270 an additional part of the hypothesis-generating process in which each model encodes a distinct set of ecological
271 assumptions. The inferred topology and dynamics of a food web therefore reflect not only ecological data, but
272 the theoretical assumptions embedded in the reconstruction framework. Disagreement among models does
273 not imply that any single approach is ‘wrong’, but rather that different models capture different facets of
274 ecological reality (Petchey et al., 2011; Stouffer, 2019). Disagreement among models does not imply that any
275 single approach is ‘incorrect’. Rather, different models capture different facets of ecological constraint—trait
276 compatibility, energetic optimisation, or topological regularity. The critical point is that these facets are not
277 interchangeable.

278 This perspective reframes reconstruction choice as part of hypothesis specification. Researchers must align
279 reconstruction approaches with the ecological signals of interest (whether potential interactions, realised
280 diets, or macro-scale structural properties) rather than treating model selection as a technical convenience.
281 Viewed through the lens of accuracy and precision, our results indicate that some network-based inferences
282 are relatively robust across reconstruction approaches, whereas others remain intrinsically uncertain. High-
283 level extinction rankings were broadly convergent, suggesting relative accuracy at coarse resolution, but
284 interaction-level details and temporal cascade dynamics diverged substantially, indicating limited precision

285 in reconstructing the fine structure of collapse. Recognising and explicitly accounting for this distinction
286 is essential if food web ecology is to move beyond descriptive reconstruction toward rigorous comparative
287 inference.

288 4.3 Implications for comparative biogeography and global change research

289 Network approaches are increasingly applied to examine how ecological organisation varies across latitudinal
290 gradients, environmental filters, disturbance regimes, and climate-driven transitions (Gilman et al., 2010;
291 Tylianakis et al., 2008). In global change ecology, networks are used to project vulnerability under warming,
292 quantify rewiring of interactions, and assess stability under species loss (*e.g.*, Hao et al., 2025; Marjakangas et
293 al., 2025). These studies frequently interpret variation in connectance, trophic height, interaction -diversity,
294 or robustness as indicators of ecological differentiation among regions or time intervals (*e.g.*, Pellissier et al.,
295 2018; Trøjelsgaard & Olesen, 2016). Our results show that such differences can systematically alter inferred
296 topology and disturbance dynamics even when species composition is held constant. This suggests that
297 apparent differences in network structure across spatial or climate gradients may reflect variation in structural
298 priors as much as ecological process.

299 Deep-time paleo-food webs provide a complementary perspective because they capture ecosystem responses to
300 large-scale environmental perturbations and extinction events under past climate change (*e.g.*, Dunhill et al.
301 (2024); Smith et al. (2025)). Fossil networks therefore represent natural experiments for evaluating resilience,
302 trophic reorganisation, and recovery following extreme environmental change. Studies of fossil food webs have
303 demonstrated how network structure mediates extinction cascades and post-disturbance reassembly (Dunne
304 et al., 2008; Roopnarine, 2006), providing empirical constraints on long-term ecological stability.

305 However, our results emphasise that even in deep-time systems structural conclusions remain sensitive
306 to modelling assumptions. Treating reconstructed networks as ensembles rather than single deterministic
307 representations provides a more transparent framework for incorporating uncertainty into comparative
308 macroecology and for using paleo data to inform expectations about modern climate-driven reorganisation.

309 4.4 Toward a more explicit modelling paradigm in food web ecology

310 The broader implication is not that any single reconstruction framework is ‘correct’ or ‘incorrect’. Rather, each
311 model class represents a distinct hypothesis about how interactions are constrained—by trait compatibility,
312 energetic optimisation, or topological regularity (Petchey et al., 2011). Food web reconstruction is therefore
313 theory-laden. Making this explicit shifts reconstruction from a preparatory step to a central component of
314 ecological modelling.

315 A mature modelling paradigm in food web ecology would treat structural priors as testable assumptions,
316 incorporate probabilistic link inference where possible, and quantify the sensitivity of macroecological
317 conclusions to alternative representations of interaction structure. Such an approach aligns with recent
318 advances in probabilistic and ensemble network modelling and would strengthen the interpretability of
319 network-based inference under global change (Banville et al., 2025; Baskerville et al., 2011; Elmasri et al.,
320 2020; Perez-Lamarque et al., 2026; Poisot et al., 2016).

321 5 Conclusions

322 Ecological network reconstruction is not a neutral technical procedure but a theoretical act that shapes
323 ecological inference. By applying six contrasting reconstruction frameworks to an identical species pool, we
324 show that structural priors systematically influence inferred food-web topology, interaction identity, and
325 disturbance dynamics. Some coarse-grained patterns, such as relative species vulnerability, are comparatively
326 robust across representations. In contrast, fine-scale interaction structure and cascade pathways are highly
327 contingent on modelling assumptions. The reliability of network-based inference is therefore scale dependent.

328 These results challenge the implicit assumption that reconstructed networks are structurally commensurable
329 across systems — whether comparing modern communities across environmental gradients or fossil assem-
330 blages across extinction intervals. When reconstruction frameworks differ, variation in connectance, trophic
331 organisation, robustness, or interaction turnover may reflect embedded modelling assumptions as much as
332 ecological processes. Network reconstruction should thus be treated as an explicit component of hypothesis
333 specification in comparative macroecology and biogeography.

334 No single model captures the full complexity of ecological organisation, but neither are alternative models
335 interchangeable. Aligning reconstruction framework with inferential goals, standardising approaches across
336 comparative studies, and incorporating ensemble or probabilistic representations will be essential for strength-
337 ening the interpretability of network analyses across spatial and temporal gradients, including efforts to
338 use deep-time systems to inform expectations under contemporary climate change. As ecological networks
339 increasingly inform global change research, recognising model reconstruction as fundamental determinants of
340 inference is critical for advancing food web ecology from descriptive reconstruction toward rigorous comparative
341 synthesis.

342 References

- 343 Allesina, S., & Tang, S. (2012). Stability criteria for complex ecosystems. *Nature*, 483(7388), 205–208.
344 <https://doi.org/10.1038/nature10832>
- 345 Bambach, R. K., Bush, A. M., & Erwin, D. H. (2007). Autecology and the filling of ecospace: Key metazoan
346 radiations. *Palaeontology*, 50(1), 1–22. <https://doi.org/10.1111/j.1475-4983.2006.00611.x>
- 347 Banville, F., Strydom, T., Blyth, P. S. A., Brimacombe, C., Catchen, M. D., Dansereau, G., Higino, G.,
348 Malpas, T., Mayall, H., Norman, K., Gravel, D., & Poisot, T. (2025). Deciphering probabilistic species
349 interaction networks. *Ecology Letters*, 28(6), e70161. <https://doi.org/10.1111/ele.70161>
- 350 Baskerville, E. B., Dobson, A. P., Bedford, T., Allesina, S., Anderson, T. M., & Pascual, M. (2011). Spatial
351 guilds in the serengeti food web revealed by a bayesian group model. *PLOS Computational Biology*, 7(12),
352 e1002321. <https://doi.org/10.1371/journal.pcbi.1002321>
- 353 Bezanson, J., Edelman, A., Karpinski, S., & Shah, V. B. (2017). Julia: A fresh approach to numerical
354 computing. *SIAM Review*, 59(1), 65–98. <https://doi.org/10.1137/141000671>
- 355 Brose, U., Jonsson, T., Berlow, E. L., Warren, P., Banasek-Richter, C., Bersier, L.-F., Blanchard, J. L., Brey,
356 T., Carpenter, S. R., Blandenier, M.-F. C., Cushing, L., Dawah, H. A., Dell, T., Edwards, F., Harper-Smith,
357 S., Jacob, U., Ledger, M. E., Martinez, N. D., Memmott, J., ... Cohen, J. E. (2006). Consumer–resource
358 body-size relationships in natural food webs. *Ecology*, 87(10), 2411–2417. [https://doi.org/https://doi.org/10.1890/0012-9658\(2006\)87%5B2411:CBRINF%5D2.0.CO;2](https://doi.org/https://doi.org/10.1890/0012-9658(2006)87%5B2411:CBRINF%5D2.0.CO;2)
- 360 Carstensen, D. W., Sabatino, M., Trøjelsgaard, K., & Morellato, L. P. C. (2014). Beta diversity of plant–
361 pollinator networks and the spatial turnover of pairwise interactions. *PLOS ONE*, 9(11), e112903.
362 <https://doi.org/10.1371/journal.pone.0112903>
- 363 Catchen, M. D., Lin, M., Poisot, T., Rolnick, D., & Gonzalez, A. (2023). *Improving ecological connectivity
364 assessments with transfer learning and function approximation*. <https://ecoenvorxiv.org/repository/view/5348/>
- 366 Curtsdotter, A., Binzer, A., Brose, U., De Castro, F., Ebenman, B., Eklöf, A., Riede, J. O., Thierry, A., & Rall,
367 B. C. (2011). Robustness to secondary extinctions: Comparing trait-based sequential deletions in static and
368 dynamic food webs. *Basic and Applied Ecology*, 12(7), 571–580. <https://doi.org/10.1016/j.baae.2011.09.008>
- 369 Delmas, E., Besson, M., Brice, M.-H., Burkle, L. A., Dalla Riva, G. V., Fortin, M.-J., Gravel, D., Guimarães, P.
370 R., Hembry, D. H., Newman, E. A., Olesen, J. M., Pires, M. M., Yeakel, J. D., & Poisot, T. (2018). Analysing
371 ecological networks of species interactions. *Biological Reviews*, 112540. <https://doi.org/10.1111/brv.12433>
- 372 Dunhill, A. M., Zarzyczny, K., Shaw, J. O., Atkinson, J. W., Little, C. T. S., & Beckerman, A. P. (2024).
373 Extinction cascades, community collapse, and recovery across a mesozoic hyperthermal event. *Nature*

- 374 *Communications*, 15(1), 8599. <https://doi.org/10.1038/s41467-024-53000-2>
- 375 Dunne, J. A., Labandeira, C. C., & Williams, R. J. (2014). Highly resolved early eocene food webs show
376 development of modern trophic structure after the end-cretaceous extinction. *Proceedings of the Royal
377 Society B: Biological Sciences*, 281(1782), 20133280. <https://doi.org/10.1098/rspb.2013.3280>
- 378 Dunne, J. A., Williams, R. J., Martinez, N. D., Wood, R. A., & Erwin, D. H. (2008). Compilation and network
379 analyses of cambrian food webs. *PLOS Biology*, 6(4), e102. <https://doi.org/10.1371/journal.pbio.0060102>
- 380 Dunne, J. A., Williams, R. J., & Martinez, N. D. (2002). Network structure and biodiversity loss in food
381 webs: Robustness increases with connectance. *Ecol. Lett.*, 5(4), 558–567.
- 382 Elmasri, M., Farrell, M. J., Davies, T. J., & Stephens, D. A. (2020). A hierarchical bayesian model for
383 predicting ecological interactions using scaled evolutionary relationships. *The Annals of Applied Statistics*,
384 14(1), 221–240. <https://doi.org/10.1214/19-AOAS1296>
- 385 Erdős, P., & Rényi, A. (1959). On random graphs. i. *Publicationes Mathematicae Debrecen*, 6(3-4), 290–297.
386 <https://doi.org/10.5486/pmd.1959.6.3-4.12>
- 387 Fricke, E. C., Hsieh, C., Middleton, O., Gorczynski, D., Cappello, C. D., Sanisidro, O., Rowan, J., Svenning,
388 J.-C., & Beaudrot, L. (2022). Collapse of terrestrial mammal food webs since the late pleistocene. *Science*,
389 377(6609), 1008–1011. <https://doi.org/10.1126/science.abn4012>
- 390 Fründ, J., McCann, K. S., & Williams, N. M. (2016). Sampling bias is a challenge for quantifying specialization
391 and network structure: Lessons from a quantitative niche model. *Oikos*, 125(4), 502–513. <https://doi.org/10.1111/oik.02256>
- 393 Gauzens, B., Brose, U., Delmas, E., & Berti, E. (2023). ATNr: Allometric trophic network models in r.
394 *Methods in Ecology and Evolution*, 14(11), 2766–2773. <https://doi.org/10.1111/2041-210X.14212>
- 395 Gauzens, B., Thouvenot, L., Srivastava, D. S., Kratina, P., Romero, G. Q., Berti, E., O’Gorman, E. J.,
396 González, A. L., Dézerald, O., Eisenhauer, N., Pires, M., Ryser, R., Farjalla, V. F., Rogy, P., Brose, U.,
397 Petermann, J. S., Geslin, B., & Hines, J. (2025). Tailoring interaction network types to answer different
398 ecological questions. *Nature Reviews Biodiversity*, 1–10. <https://doi.org/10.1038/s44358-025-00056-7>
- 399 Gilman, S. E., Urban, M. C., Tewksbury, J., Gilchrist, G. W., & Holt, R. D. (2010). A framework
400 for community interactions under climate change. *Trends in Ecology & Evolution*, 25(6), 325–331.
401 <https://doi.org/10.1016/j.tree.2010.03.002>
- 402 Gravel, D., Baiser, B., Dunne, J. A., Kopelke, J.-P., Martinez, N. D., Nyman, T., Poisot, T., Stouffer, D. B.,
403 Tylianakis, J. M., Wood, S. A., & Roslin, T. (2019). Bringing elton and grinnell together: A quantitative
404 framework to represent the biogeography of ecological interaction networks. *Ecography*, 42(3), 401–415.
405 <https://doi.org/https://doi.org/10.1111/ecog.04006>
- 406 Guimarães, P. R. (2020). The structure of ecological networks across levels of organization. *Annual Review of*

- 407 *Ecology, Evolution, and Systematics*, 51(1). <https://doi.org/10.1146/annurev-ecolsys-012220-120819>
- 408 Hao, X., Holyoak, M., Zhang, Z., & Yan, C. (2025). Global projection of terrestrial vertebrate food webs
409 under future climate and land-use changes. *Global Change Biology*, 31(2), e70061. <https://doi.org/10.1111/gcb.70061>
- 410 1111/gcb.70061
- 411 Jordano, P. (2016). Sampling networks of ecological interactions. *Functional Ecology*. <https://doi.org/10.1111/1365-2435.12763>
- 412 1111/1365-2435.12763
- 413 Kemp, D. B., Han, Z., Hu, X., Chen, W., Jin, S., Izumi, K., Yan, Q., Baranyi, V., Jin, X., Corso, J. D., & Ge,
414 Y. (2024). Global hydroclimate perturbations during the toarcian oceanic anoxic event. *Earth-Science
Reviews*, 258, 104946. <https://doi.org/10.1016/j.earscirev.2024.104946>
- 415 258, 104946. https://doi.org/10.1016/j.earscirev.2024.104946
- 416 Marjakangas, E.-L., Dalsgaard, B., & Ordóñez, A. (2025). Fundamental interaction niches: Towards
417 a functional understanding of ecological networks' resilience. *Ecology Letters*, 28(6), e70146. <https://doi.org/10.1111/ele.70146>
- 418 //doi.org/10.1111/ele.70146
- 419 Michalska-Smith, M. J., & Allesina, S. (2019). Telling ecological networks apart by their structure: A
420 computational challenge. *PLOS Computational Biology*, 15(6), e1007076. <https://doi.org/10.1371/journal.pcbi.1007076>
- 421 1007076
- 422 Milo, R., Shen-Orr, S., Itzkovitz, S., Kashtan, N., Chklovskii, D., & Alon, U. (2002). Network motifs: Simple
423 building blocks of complex networks. *Science*, 298(5594), 824–827. <https://doi.org/10.1126/science.298.5594.824>
- 424 5594.824
- 425 Morales-Castilla, I., Matias, M. G., Gravel, D., & Araújo, M. B. (2015). Inferring biotic interactions from
426 proxies. *Trends in Ecology & Evolution*, 30(6), 347–356. <https://doi.org/10.1016/j.tree.2015.03.014>
- 427 30(6), 347–356. https://doi.org/10.1016/j.tree.2015.03.014
- 428 Pellissier, L., Albouy, C., Bascompte, J., Farwig, N., Graham, C., Loreau, M., Magliañesi, M. A., Melián, C.
429 J., Pitteloud, C., Roslin, T., Rohr, R., Saavedra, S., Thuiller, W., Woodward, G., Zimmermann, N. E.,
430 & Gravel, D. (2018). Comparing species interaction networks along environmental gradients. *Biological
Reviews*, 93(2), 785–800. <https://doi.org/10.1111/brv.12366>
- 431 93(2), 785–800. https://doi.org/10.1111/brv.12366
- 432 Perez-Lamarque, B., Andréoletti, J., Morillon, B., Pion-Piola, O., Lambert, A., & Morlon, H. (2026). Darwin's
433 entangled bank through deep time: Structural stability of mutualistic networks over large geographic and
434 temporal scales. *EcoEvoRxiv*. <https://doi.org/10.1101/2025.10.08.681159>
- 435 10.1101/2025.10.08.681159
- 436 0710672105
- 437 Perez, O. L., Beckerman, A. P., Riede, J. O., & Warren, P. H. (2008). Size, foraging, and food web structure.
438 *Proceedings of the National Academy of Sciences*, 105(11), 4191–4196. <https://doi.org/10.1073/pnas.0710672105>
- 439 10.1073/pnas.0710672105
- 437 Perez, O. L., Beckerman, A. P., Riede, J. O., & Warren, P. H. (2011). Fit, efficiency, and biology:
438 Some thoughts on judging food web models. *Journal of Theoretical Biology*, 279(1), 169–171. <https://doi.org/10.1016/j.jtbi.2011.03.019>
- 439 279(1), 169–171. https://doi.org/10.1016/j.jtbi.2011.03.019

- 440 Pichler, M., & Hartig, F. (2023). Machine learning and deep learning—a review for ecologists. *Methods in*
441 *Ecology and Evolution*, 14(4), 994–1016. <https://doi.org/10.1111/2041-210X.14061>
- 442 Poisot, T., Bergeron, G., Cazelles, K., Dallas, T., Gravel, D., MacDonald, A., Mercier, B., Violet, C., &
443 Vissault, S. (2021). Global knowledge gaps in species interaction networks data. *Journal of Biogeography*,
444 jbi.14127. <https://doi.org/10.1111/jbi.14127>
- 445 Poisot, T., Canard, E., Mouillot, D., Mouquet, N., & Gravel, D. (2012). The dissimilarity of species interaction
446 networks. *Ecology Letters*, 15(12), 1353–1361. <https://doi.org/10.1111/ele.12002>
- 447 Poisot, T., Cirtwill, A., Cazelles, K., Gravel, D., Fortin, M.-J., & Stouffer, D. (2016). The structure of
448 probabilistic networks. *Methods in Ecology and Evolution*, 7(3), 303312. <https://doi.org/10>
- 449 Poisot, T., & Gravel, D. (2014). When is an ecological network complex? Connectance drives degree
450 distribution and emerging network properties. *PeerJ*, 2, e251. <https://doi.org/10.7717/peerj.251>
- 451 Poisot, T., Stouffer, D. B., & Gravel, D. (2015). Beyond species: Why ecological interaction networks vary
452 through space and time. *Oikos*, 124(3), 243–251. <https://doi.org/10.1111/oik.01719>
- 453 R Core Team. (2024). *R: A language and environment for statistical computing*. R Foundation for Statistical
454 Computing. <https://www.R-project.org/>
- 455 Rohr, R., Scherer, H., Kehrli, P., Mazza, C., & Bersier, L.-F. (2010). Modeling food webs: Exploring
456 unexplained structure using latent traits. *The American Naturalist*, 176(2), 170–177. <https://doi.org/10.1086/653667>
- 458 Roopnarine, P. D. (2006). Extinction cascades and catastrophe in ancient food webs. *Paleobiology*, 32(1),
459 1–19. <https://www.jstor.org/stable/4096814>
- 460 Sandra, H.-P., Traveset, A., Nogales, M., Heleno, R., Llewelyn, J., & Strona, G. (2025). Sampling biases
461 across interaction types affect the robustness of ecological multilayer networks. *Ecological Informatics*,
462 103183. <https://doi.org/10.1016/j.ecoinf.2025.103183>
- 463 Shaw, J. O., Dunhill, A. M., Beckerman, A. P., Dunne, J. A., & Hull, P. M. (2024). *A framework for*
464 *reconstructing ancient food webs using functional trait data* (p. 2024.01.30.578036). bioRxiv. <https://doi.org/10.1101/2024.01.30.578036>
- 466 Smith, Q. A., Tomé, C. P., Gearty, W., Smith, F. A., Shizuka, D., & Lyons, S. K. (2025). Consequences
467 of the megafauna extinction: Changes in food web networks on the edwards plateau across the pleis-
468 tocene–holocene transition. *Global Ecology and Biogeography*, 34(12), e70113. <https://doi.org/10.1111/geb.70113>
- 470 Solé, R. V., & Montoya, M. (2001). Complexity and fragility in ecological networks. *Proceedings of the Royal*
471 *Society of London. Series B: Biological Sciences*, 268(1480), 2039–2045. <https://doi.org/10.1098/rspb.2001.1767>

- 473 Stouffer, D. B. (2019). All ecological models are wrong, but some are useful. *Journal of Animal Ecology*,
474 88(2), 192–195. [https://doi.org/https://doi.org/10.1111/1365-2656.12949](https://doi.org/10.1111/1365-2656.12949)
- 475 Stouffer, D. B., Camacho, J., Jiang, W., & Nunes Amaral, L. A. (2007). Evidence for the existence of a robust
476 pattern of prey selection in food webs. *Proceedings of the Royal Society B: Biological Sciences*, 274(1621),
477 1931–1940. <https://doi.org/10.1098/rspb.2007.0571>
- 478 Strydom, T., Catchen, M. D., Banville, F., Caron, D., Dansereau, G., Desjardins-Proulx, P., Forero-Muñoz,
479 N. R., Higino, G., Mercier, B., Gonzalez, A., Gravel, D., Pollock, L., & Poisot, T. (2021). A roadmap
480 towards predicting species interaction networks (across space and time). *Philosophical Transactions of the
481 Royal Society B: Biological Sciences*, 376(1837), 20210063. <https://doi.org/10.1098/rstb.2021.0063>
- 482 Strydom, T., Dunhill, A. M., Dunne, J. A., Poisot, T., & Beckerman, A. P. (2026). Scaling from metawebs
483 to realised webs: A hierarchical approach to network ecology. *EcoEvoRxiv*. <https://doi.org/10.32942/X2JW8K>
- 485 Thuiller, W., Calderón-Sanou, I., Chalmandrier, L., Gaüzère, P., O'Connor, L. M. J., Ohlmann, M., Poggiato,
486 G., & Münkemüller, T. (2024). Navigating the integration of biotic interactions in biogeography. *Journal
487 of Biogeography*, 51(4), 550–559. <https://doi.org/10.1111/jbi.14734>
- 488 Trøjelsgaard, K., & Olesen, J. M. (2016). Ecological networks in motion: Micro- and macroscopic variability
489 across scales. *Functional Ecology*, 30(12), 1926–1935. <https://doi.org/https://doi.org/10.1111/1365-2435.12710>
- 491 Tylianakis, J. M., Didham, R. K., Bascompte, J., & Wardle, D. A. (2008). Global change and species
492 interactions in terrestrial ecosystems. *Ecology Letters*, 11(12), 1351–1363. <https://doi.org/10.1111/j.1461-0248.2008.01250.x>
- 494 Tylianakis, J. M., & Morris, R. J. (2017). Ecological networks across environmental gradients. *Annual Review of
495 Ecology, Evolution, and Systematics*, 48(1), 25–48. <https://doi.org/10.1146/annurev-ecolsys-110316-022821>
- 496 Williams, R. J., & Martinez, N. D. (2004). Stabilization of chaotic and non-permanent food-web dynamics.
497 *The European Physical Journal B - Condensed Matter*, 38(2), 297–303. <https://doi.org/10.1140/epjb/e2004-00122-1>
- 499 Williams, R. J., & Martinez, N. D. (2000). Simple rules yield complex food webs. *Nature*, 404(6774), 180–183.
500 <https://doi.org/10.1038/35004572>
- 501 Williams, R. J., & Martinez, N. D. (2008). Success and its limits among structural models of complex food
502 webs. *The Journal of Animal Ecology*, 77(3), 512–519. <https://doi.org/10.1111/j.1365-2656.2008.01362.x>
- 503 Yeakel, J. D., Pires, M. M., Rudolf, L., Dominy, N. J., Koch, P. L., Guimarães, P. R., & Gross, T.
504 (2014). Collapse of an ecological network in ancient egypt. *PNAS*, 111(40), 14472–14477. <https://doi.org/10.1073/pnas.1408471111>

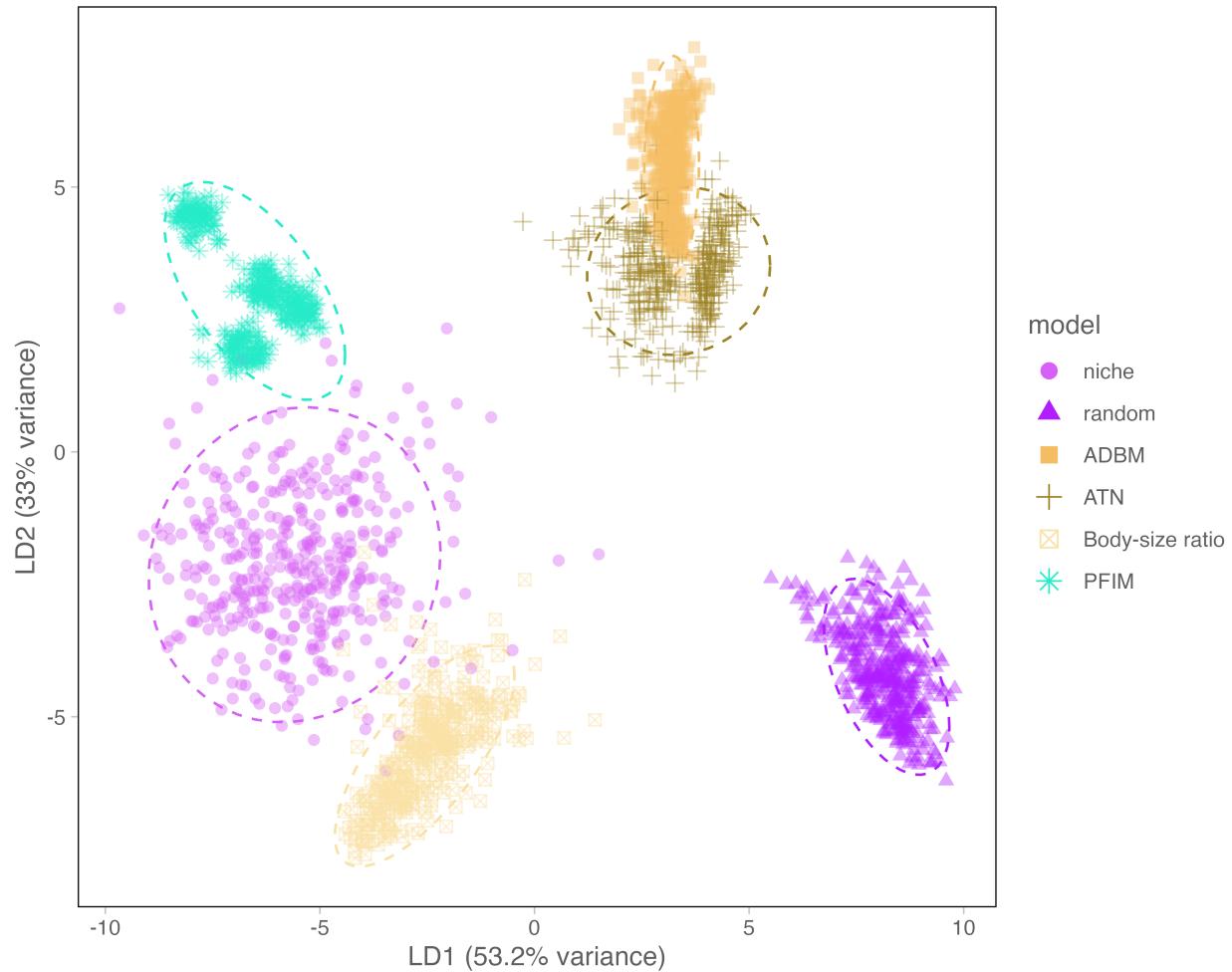


Figure 1: Linear discriminant analysis (LDA) of ecological network metrics for six model types. Each point represents a replicate, and ellipses indicate 95% confidence regions for each model. The second column represents the correlation of the various network metrics with the respective LDA axes.

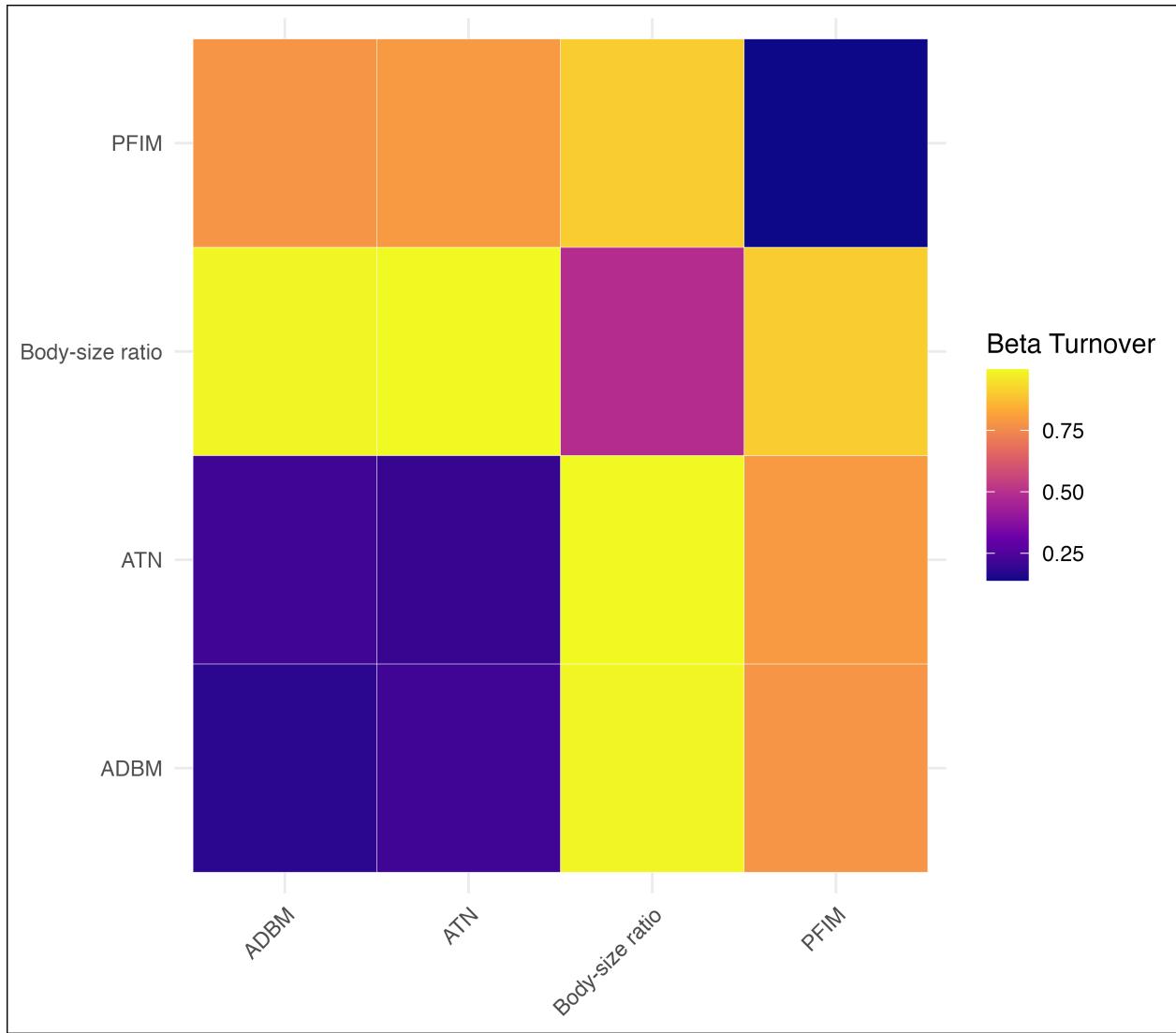


Figure 2: Pairwise β -turnover in species interactions among four ecological network models (ADBM, ATN, Body-size ratio, and PFIM). Each cell represents the mean turnover value between a pair of models, with warmer colours indicating greater dissimilarity in inferred interactions. The diagonal is omitted. High turnover values (yellow) indicate strong disagreement in network structure between models, whereas lower values (blue–purple) indicate greater similarity.

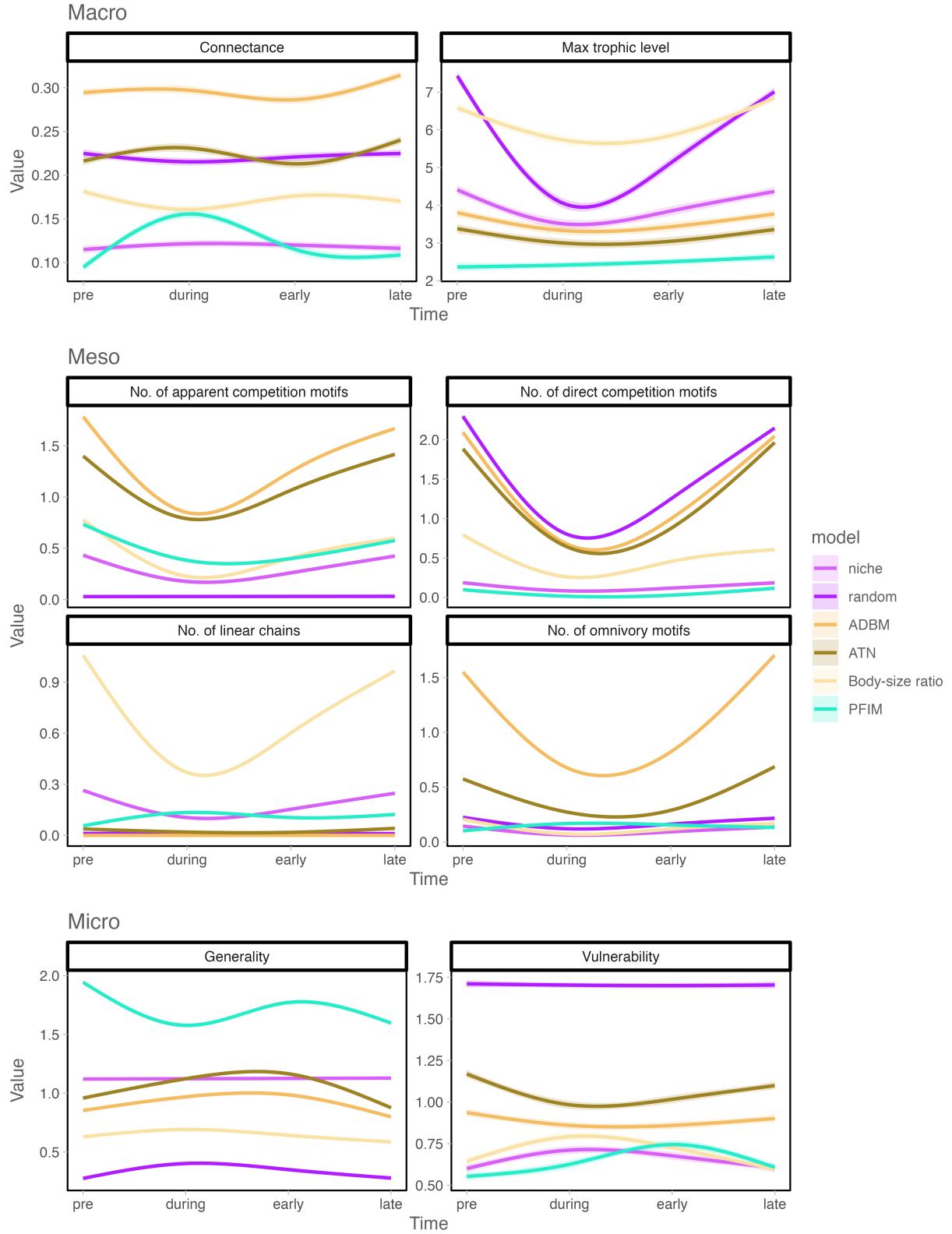


Figure 3: GAM-predicted trajectories of network structure during extinction simulations reveal pronounced differences in the timing and magnitude of change across reconstruction models. Lines show model-specific smooths and shaded areas indicate 95% confidence intervals. Deterministic approaches produce smoother, more consistent dynamics, whereas stochastic models exhibit greater variability, underscoring the sensitivity of inferred collapse pathways to reconstruction assumptions.

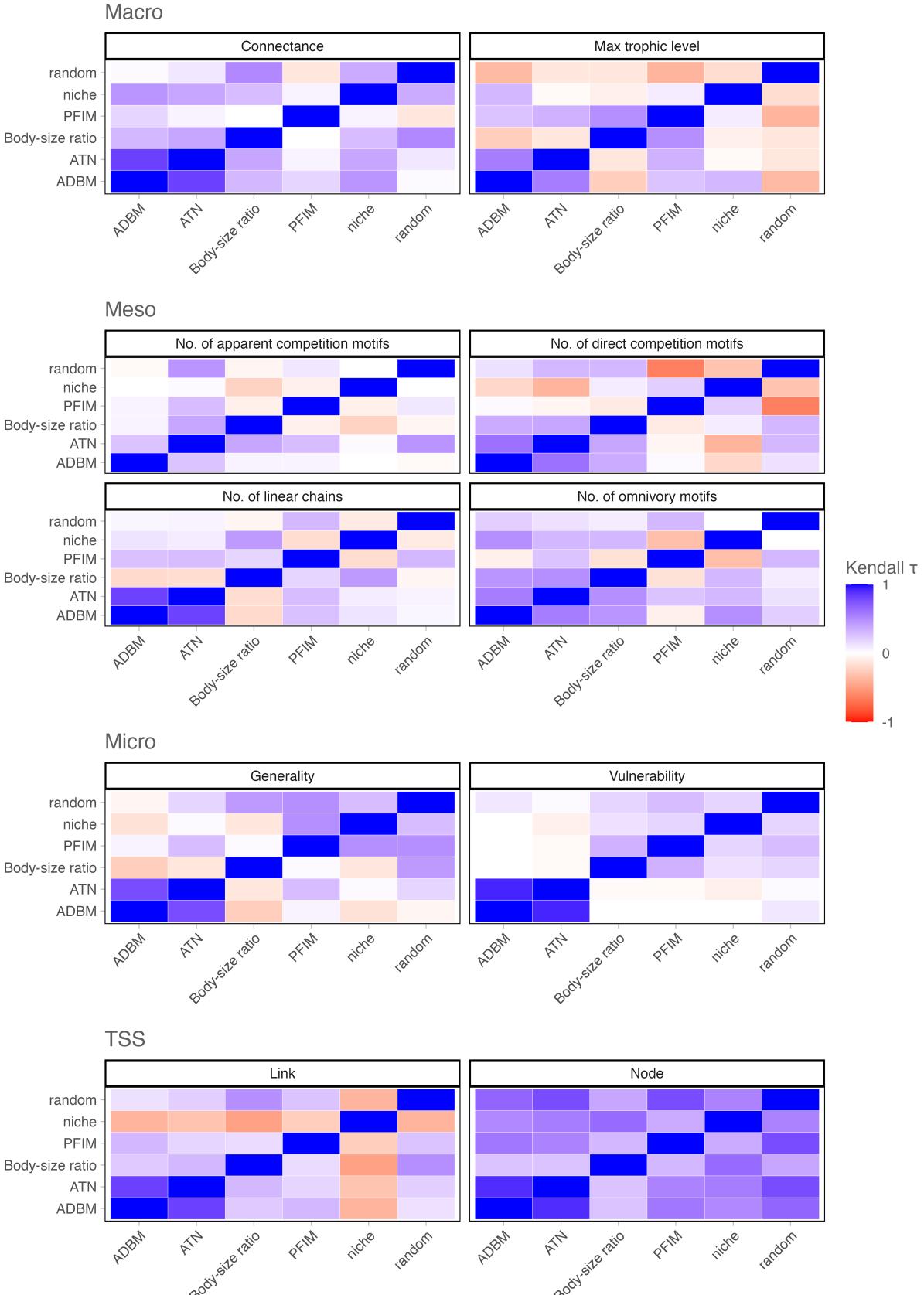


Figure 4: Heatmaps showing pairwise Kendall rank correlation coefficients (τ) between models for each network metric. Each panel corresponds to a different metric and displays the degree of agreement in extinction-scenario rankings across models based on mean absolute differences (MAD) between observed and predicted network values. Positive τ values (blue) indicate concordant rankings between models, whereas negative τ values (red) indicate opposing rankings. Warmer colours approaching zero represent little or no agreement. Panels