

Methods for Reconstructing Paleo Food Webs

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Abstract: Food webs represent the feeding relationships between species and can help infer ecosystem-level processes. Alongside the development of food web theory, methods for constructing food webs have been developed to infer species interactions when empirical data is lacking. Food web construction methods are diverse, each utilising different approaches to infer species interactions —such as the use of traits to infer mechanistic relationships vs using gut content as a proxy for species diets. These methods have distinct theories, mechanisms, and data requirements. In paleoecology, where direct evidence of feeding interactions are rare, food web construction methods are especially valuable and affords us the opportunity to make inferences about paleo communities beyond simply a record of species composition. However, the limitations of paleontological data (e.g., information of species traits is limited to that which can be preserved) restrict which methods can reliably be used. By considering both ecological theory and the constraints of what can be derived from the fossil record, we identify the methods best suited for the construction of paleo food webs. Specifically, we focus on how these methods differ in the networks they produce and what these networks can reveal about species interactions. In doing so we hope to clarify the ecological nuances of network prediction and help prevent the accidental misuse or misinterpretation of paleo food webs.

Keywords: food web, network construction

¹ 1 Why paleo food webs?

² There has been a growing interest in the idea of using past (deep time) historic events/changes as a means to
³ help inform current conservation decisions list some egs(Dillon et al., 2022; Kiessling et al., 2019). The use of
⁴ species interactions and networks to help us understand aspects of community composition has gained an
⁵ interest in contemporary settings (eg the thullier paper and ??) and so it is perhaps unsurprising that there
⁶ has been a growing interest in using paleo food webs in a similar manner (*e.g., * Dunhill et al., 2024; Hao et
⁷ al., 2025; Yeakel et al., 2014). However, one of the core challenges and limitations of being able to *use* food
⁸ webs to answer ecological questions is the challenge of constructing them (Jordano, 2016), a challenge which
⁹ is compounded when using paleo data as we are limited by that which has been preserved in the fossil record
¹⁰ and often interactions are constructed by expert opinion (*e.g., * Dunne et al., 2014). The challenges with
¹¹ recording species interaction networks has driven the development of a large number of models and tools that
¹² can be used to infer either species interactions (see *e.g.*, Morales-Castilla et al., 2015; Pichler & Hartig, 2023;
¹³ Strydom et al., 2021a for broader reviews) or networks (see *e.g.*, Allesina et al., 2008 (it is one of the more
¹⁴ complete review of methods IMO)). Although progress has been made on the development of tools that are
¹⁵ specific for constructing paleo webs (Fricke et al., 2022; Roopnarine, 2006; *e.g., * Shaw et al., 2024) there is
¹⁶ value in identifying a broader suite of methods that can be (appropriately) used for paleo communities (these
¹⁷ are methods that are amenable to the data constraints that are prevalent in paleo communities in terms of
¹⁸ both the completeness of fossil records as well as how the deeper in time we move the further away we might
¹⁹ be moving from contemporary analogs. Secondly it should also be noted that different network construction
²⁰ approaches are encoding different processes (Strydom, in prep) and there is value in showcasing how the
²¹ networks construct models may differ.

²² Here we: want to identify the differences between models that predict interactions (and thus metawebs), and
²³ models that predict network structure. Specifically we want to look at 1) the structural difference between all
²⁴ models (*i.e.*, do we see a difference in the distribution of links between networks that have the same number
²⁵ of nodes?) and 2) the identity of pairwise links between species pairs (*i.e.*, do different models differ in which
²⁶ links are present (or absent) between species pairs?) Additionally we want to establish if using networks that
²⁷ are constructed using different models will change the the downstream inferences that are made for this we
²⁸ use the work from Dunhill et al. (2024). as a case study

²⁹ **2 Contextualising the prediction of paleo webs within the contem-**

³⁰ **porary toolbox**

³¹ There is an evolving body of work that focuses on developing tools specifically for the task of predicting food
³² webs. However as highlighted in Strydom (in prep) it is important that we understand what assumptions
³³ are being embedded within the network as a result of the underlying philosophy which a model was built on.
³⁴ Broadly we can think about models that are nested within two different schools of thought. This includes
³⁵ models that focus on assessing the *mechanistic* feasibility of an interaction being able to occur between two
³⁶ species or models that are more closely married to specific bodies of ecological *theory* - such as niche theory or
³⁷ foraging ecology. Broadly speaking the difference between these two modeling approaches is that mechanistic
³⁸ models typically asses interactions at a pairwise level but determining is an interaction is feasible between
³⁹ a species *pair* (extended *e.g.*, here), whereas theoretical models typically use some set of assumptions to
⁴⁰ constrain the distribution of links at the *community* scale (extended *e.g.*, here probably niche model or DBM).
⁴¹ Models that have specifically been developed in the paleo space tend to be mechanistic models (Shaw et al.
⁴² (2024); Roopnarine (2006); Fricke et al. (2022)) which means that there is a whole type of network that is
⁴³ typically not being created for paleo communities (theoretical/realised ones). However, there is an argument
⁴⁴ that the theoretical models that have been developed in contemporary settings should hold even for paleo
⁴⁵ communities since we expect the ‘fundamental currencies of life’ to remain constant - *e.g.*, the energetic
⁴⁶ constraints of foraging or foraging niches (is that the right way to phrase it). Somehow close this out by going
⁴⁷ from we should be able to use contemporary models we need to think about the constraints that are typically
⁴⁸ placed on us by paleo data as well as the assumptions that some of these models might require us to make
⁴⁹ (*e.g.* the niche model makes some heavy assumptions by constraining the connectance - which itself is often
⁵⁰ used as a metric to understand changes or differences in network structure).

⁵¹ Introduce here that it is thus important to understand that not all contemporary models may actually be
⁵² suitable for paleo contexts as the assumptions that they make (or the data that they require) may actually
⁵³ introduce uncertainty/errors into the resulting network rendering them of little use. As a simple example
⁵⁴ the framework developed by Fricke et al. (2022) uses phylogenetic relatedness as a way to infer interactions
⁵⁵ of Pleistocene mammals by looking at their extant relatives. Although this approach is ecologically sound
⁵⁶ (phylogenetic relatedness is also used in other approaches *e.g.*, Strydom et al. (2022)) there is also an argument
⁵⁷ that the further back in evolutionary time we go (and the greater the phylogenetic distance between extant
⁵⁸ and extinct communities become) there is more uncertainty introduced by the phylogenetic tree than what is
⁵⁹ introduced by assuming that interactions will be phylogenetically conserved. On the other side of the coin it

60 can be very challenging to determine traits from the fossil record and so it may be instead by more pragmatic
61 to use models that are completely agnostic to the identity of the species and are instead concerned with
62 the network structure (*e.g.*, the niche model developed by Williams & Martinez (2008)). Fundamentally this
63 means that there is a trade off between the data that is available and the type of network one is interested in
64 creating.

65 **3 Understanding how networks are different**

66 It is important to be aware that networks can be configured in different ways depending on how the interactions
67 are defined (Strydom, in prep). Basically we have metawebs (which represent *potential* interactions), realised
68 networks (which represent the subset of potential that are realised as a result of community and environmental
69 context), and structural networks (species agnostic networks that are structurally informative). Here also
70 talk about the implications of these different networks types - different uses and capturing different processes.
71 Specifically link this to models - *i.e.*, different models have been developed to construct a *specific* network
72 representation.

73 Think about the axes - trait-based/mechanistic model (metawebs) and then we have the statistical/theoretical
74 models (which have their own mini axis of regression vs full theory models...)

75 Need to link to Gauzens et al. (2025) here.

76 **4 Challenges specific to building paleo networks**

77 Although there has been a push for the development of tools and methods that allow us to predict species
78 interactions and networks [see *e.g.*, XXX for some reviews] they will not all be suitable for the prediction of
79 paleo communities. This is primarily due to limitations that we are faced with in terms of the information
80 that can be inferred from the fossil record (such as species traits abundances, and assemblages), which is
81 needed as input data for the different models. The limited information available from the fossil record is
82 compounded by the incomplete and biased preservation of species [REF], the spatial ambiguity of fossils
83 found in a location [were species conserved *in situ* or were they there owing to geological processes; REF],
84 and an increasing degree of ‘fuzziness’ the further one moves back in geological time [our understanding
85 of both phylogenetic and functional trait space, REF]. Methodologically speaking some tools that ‘learn’
86 from contemporary communities (*e.g.*, Strydom et al. (2023), Caron et al. (2022)) will become ‘worse’ the
87 further one goes back in time since species then look very different from now but can still be useful for ‘recent’
88 communities (*e.g.*, Fricke et al. (2022)). This is not to say that it is impossible to construct paleo networks

89 but rather identify that there are a subset of models that are probably not at all suitable for constructing
 90 paleo networks (*e.g.*, Null models, since there are fully driven by abundance), other methods will be better
 91 suited depending on the community of interest *e.g.*, for more contemporary communities that have modern
 92 analogs we can use methods rooted in phylogeny (*e.g.*, Fricke et al. (2022), Strydom et al. (2023)) or traits
 93 (*e.g.*, Caron et al. (2022)), and then there is the third axis which is to think about which are the assumptions
 94 that are made and there trade off of that. This includes thinking about both assumptions you are making
 95 about the actual data *e.g.*, trying to extrapolate body size from fossil data but also assumptions across time
 96 *e.g.*, assuming modern trait-feeding modes are the same OR that assumptions about network structure will
 97 hold across deep time.

98 4.1 Approaches to food web prediction

99 Here we should take the time to go in and just articulate that there are nuance and differences in terms of
 100 predicting interactions vs predicting networks. Once it is finally on a preprint server we can obviously link to
 101 the T4T stuff...

102 Here we present six different models (Table 1) that can be used to construct food webs for both this specific
 103 community but are also broadly suited to paleo network prediction. These models span all facets of the
 104 network representation space (metaweb, realised, and structural network) and are suitable for an array of
 105 different paleo communities as the data requirements are ‘paleo friendly’.

Table 1: A summary of the different families of tools that can be used to generate paleo food webs.

Model family	Assumptions	Data needs	‘Limitation’	Network type	Key reference
random	Links are randomly distributed within a network	richness, number of links	parameter assumptions, species agnostic	structural network	Erdős & Rényi (1959)
niche	Networks are interval, species can be ordered on a ‘niche axis’	richness, connectance	parameter assumptions, species agnostic	structural network	Williams & Martinez (2008)

Model family	Assumptions	Data needs	'Limitation'	Network type	Key reference
allometric diet breadth model (ADBM)	Interactions are determined by energetic costs (foraging ecology)	body mass, biomass (abundance)	does not account for forbidden links in terms of trait compatibility, assumptions on body size and biomass (abundance) from fossil data	realised network	Petchey et al. (2008)
l-matrix	Interactions inferred using allometric rules (ratio of body sizes between predator and prey), with links being constrained by a Ricker function	body mass, number of producer species	does not account for forbidden links in terms of trait compatibility, assumptions on body size from fossil data, assumptions as to the number of producer species	realised network	Schneider et al. (2016)

Model family	Assumptions	Data needs	‘Limitation’	Network type	Key reference
paleo food web inference model (PFIM)	Interactions can be inferred by a mechanistic framework/relationships	feeding traits for taxa, mechanistic feeding rules	Assumption made as to the feeding mechanisms, need to elucidate traits from models (although this is a way smaller issue)	metaweb	Shaw et al. (2024)
body size ratio model	Interactions inferred using allometric rules (ratio of body sizes between predator and prey). :ogit of the linking probability used to further constrain links to an ‘optimal size range’ for prey.	body mass	does not account for forbidden links in terms of evolutionary compatibility, assumptions on body size from fossil data	metaweb??	Rohr et al. (2010)

¹⁰⁶ **4.2 Structural models**

¹⁰⁷ **4.2.1 Random model**

¹⁰⁸ The Erdős–Rényi random graph model (Erdős & Rényi, 1959) uniformly at random assigns an L number of ¹⁰⁹ links to an S number of nodes (species richness). From an ecological perspective this model assumes that the ¹¹⁰ interactions between species occurs regardless of the identity of the species (*i.e.*, species have no agency) and

111 links are randomly distributed throughout the network. This creates a food web that is as free as possible
112 from biological structuring while maintaining the expected richness (S) and connectance (L/S^2)

113 We could theoretically use the other ‘null models’ BUT I feel like in the context of constructing
114 a network for a given community the Erdős–Rényi is the better choice than the other models
115 that (IMO) are more suited to hypothesis testing e.g. do observed networks differ from the null
116 network... Whereas Erdős–Rényi really is just a case of here is a truly random network with
117 the specified number of links and nodes and anyway one of the Null models is a derivative of
118 Erdős–Rényi if I remember correctly.

119 4.2.2 Niche model

120 The niche model (Williams & Martinez, 2000) introduces the idea that species interactions are based on the
121 ‘feeding niche’ of a species. Broadly, all species are randomly assigned a ‘feeding niche’ range and all species
122 that fall in this range can be consumed by that species (thereby allowing for cannibalism). The niche of each
123 species is randomly assigned and the range of each species’ niche is (in part) constrained by the specified
124 connectance (Co) of the network. The niche model has also been modified, although it appears that adding
125 to the ‘complexity’ of the niche model does not improve on its ability to generate a more ecologically ‘correct’
126 network (Williams & Martinez, 2008).

127 Each of S species assigned a ‘niche value’ parameter n_i drawn uniformly from the interval [0,1]. Species i
128 consumes all species falling in a range (r_i) that is placed by uniformly drawing the center of the range (c_i)
129 from $[\frac{r_i}{2}, n_i]$. The size of r_i is assigned by using a beta function to randomly draw values from [0,1] whose
130 expected value is $2 \times Co$ and then multiplying that value by n_i to obtain the desired Co .

131 4.2.3 Allometric diet breadth model

132 The Allometric diet breadth model (ADBM; Petchey et al. (2008)) is rooted in feeding theory and allocates
133 the links between species based on energetics, which predicts the diet of a consumer based on energy intake.
134 This means that the model is focused on predicting not only the number of links in a network but also the
135 arrangement of these links based on the diet breadth of a species, where the diet (K) is defined as follows:

$$K = \frac{\sum_{i=1}^k \lambda_{ij} E_i}{1 + \sum_{i=1}^k \lambda_{ij} H_{ij}}$$

136 where λ_{ij} is the handling time, which is the product of the attack rate A_i and resource density N_i , E_i is the
137 energy content of the resource and H_{ij} is the ratio handling time, with the relationship being dependent on

¹³⁸ the ratio of predator and prey body mass as follows:

$$H_{ij} = \frac{h}{b - \frac{M_i}{M_j}} \text{ if } \frac{M_i}{M_j} < b$$

¹³⁹ or

$$H_{ij} = \infty \geq b$$

¹⁴⁰ Refer to Petchey et al. (2008) for more details as to how these different terms are parametrised.

¹⁴¹ 4.2.4 L matrix

¹⁴² For now we can link to the ATNr package (Gauzens et al., 2023) until I can find a more suitable manuscript
¹⁴³ that breaks down this construction method. Schneider et al. (2016) Interactions are determined by allometric
¹⁴⁴ rules (ratio of consumer (M_i) and resource (M_j) body sizes) and a Ricker function as defined by R_{opt} and
¹⁴⁵ γ and returns The probability of a link (P_{ij}) existing between a consumer and resource, and is defined as
¹⁴⁶ follows:

$$P_{ij} = (L \times \exp(1 - L))^\gamma$$

¹⁴⁷ where

$$L = \frac{M_i}{M_j \times R_{opt}}$$

¹⁴⁸ It is also possible to apply a threshold value to P_{ij} , whereby any probabilities below that threshold are set to
¹⁴⁹ zero.

¹⁵⁰ 4.3 Interaction predictions

¹⁵¹ 4.3.1 Paleo food web inference model

¹⁵² The Paleo food web inference model (PFIM; Shaw et al. (2024)) uses a series of rules for a set of trait
¹⁵³ categories (such as habitat and body size) to determine if an interaction can feasibly occur between a species
¹⁵⁴ pair. If all conditions are met for the different rule classes then an interaction is deemed to be feasible. The
¹⁵⁵ original work put forward in Shaw et al. (2024) also includes a ‘downsampling’ step developed by Roopnarine

156 (2006) that uses a power law, defined by the link distribution, to ‘prune’ down some of the links. It is worth
157 mentioning that this approach is similar to that developed by Roopnarine (2017) with the exception that
158 Shaw et al. (2024) does not specifically bin species into guilds, and so we choose to use the method developed
159 by Shaw et al. (2024) since both approaches should produce extremely similar networks as they are built on
160 the same underlying philosophy.

161 **4.3.2 Body size ratio model**

162 The body size ratio model (Rohr et al., 2010) determines the probability of feeding interactions occurring
163 between species by using the ratio between the consumer (M_i) and resource (M_j) body sizes. In order to
164 represent the predator-prey bodymass ratio as a ‘feeding niche’ the ratio is also modified by both a β and γ
165 distribution. The probability of a link existing between a consumer and resource (in its most basic form) is
166 defined as follows:

$$P_{ij} = \frac{p}{1 + p}$$

167 where

$$p = \exp[\alpha + \beta \log(\frac{M_i}{M_j}) + \gamma \log^2(\frac{M_i}{M_j})] \quad (1)$$

168 The original latent-trait model developed by Rohr et al. (2010) also included an additional latent trait term
169 $v_i \delta f_j$ however for simplicity we will use Equation 1 as per Yeakel et al. (2014). Based on Rohr et al. (2010)
170 it is possible to estimate the parameters α , δ , and γ using a GLM but we will use the parameters from Yeakel
171 et al. (2014), which was ‘trained’ on the Serengeti food web data and are as follows: $\alpha = 1.41$, $\delta = 3.75$, and
172 $\gamma = 1.87$.

173 **5 Case study: Toarcian mass extinction event**

174 **5.1 Dataset overview**

175 **5.1.1 Species occurrence**

176 Here we use the fossil occurrence data over an interval extends from the upper Pliensbachian (~185 Ma) to
177 the upper Toarcian (~175 Ma) of the Cleveland Basin (see Dunhill et al., 2024 for a more comprehensive
178 overview). The data set consists of a subset of four broad time periods (pre-extinction, post-extinction, early

recovery, and late recovery). The assemblages are treated as communities of interacting organisms. Something about the total number of taxa as well as numbers per a time period? Probably also make a comment that this is a ‘deep time’ community we are looking at.

5.1.2 Defining modes of life (traits)

We used the modes of life (traits) as identified in Dunhill et al. (2024), who defined four traits: motility (fast, slow, facultative, non-motile), tiering (pelagic, erect, surficial, semi-infaunal, shallow infaunal, deep infaunal), feeding (predator, suspension feeder, deposit feeder, mining, grazer), and size: gigantic (>500 mm), very large (>300–500 mm), large (>100–300 mm), medium (>50–100 mm), small (>10–50 mm), tiny (10 mm), for each fossil species based on the ecological traits defined in the Bambach ecospace model (Bambach et al., 2007).

5.1.3 Constructing networks

For each paleo community (time bin) we constructed **100** networks for each model (so $6 * 100$) networks. These networks were ‘simplified’ to removed any disconnected species. In total 2400 networks were constructed. When a quantitative measure of body size is needed (ADBM, bodymassratio, lmatrix) we drew a body mass for each species from a uniform distribution. The ranges were defined by the different size classes as discussed in insert cross ref to correct subsection here *e.g.*, a species classed as ‘very large’ would have a body mass drawn from $U(300, 500)$. This was repeated for each run in order to add variation to the networks constructed, however the same body sizes were kept consistent for the relevant models (adbm, bodymassratio, l-matrix) *i.e.*, an ADBM and bodymassratio network from the same rep number would have used the same bodysize. The PFIM networks were downsampled (see relevant section). For both the random and niche model the desired connectance was randomly selected between the range 0.07 - 0.15 for each repetition but kept consistent for both models. For each network we calculated the properties listed in Table 2

5.1.4 Simulating Extinctions

5.2 Do different models recover different network structures?

In terms of wanting to asses and compare across the different models it is beneficial to approach this task by thinking about the different aspects of the network as well as interactions that are being predicted by the different models. It is perhaps beneficial to think of these across different ‘scales’ of organisation within the network, namely macro (the entire network), meso (smaller interacting units within the network), and micro (species-level attributes). Although there are a myriad of possible ways to ‘measure’ and analyse ecological networks (Delmas et al., 2018) we do still lack a clear set of guidelines for assessing how well models recover

208 network structure (Allesina et al., 2008) and it is beneficial to use a small subset of metrics that can clearly
209 be tied to broader aspects of network function or capturing a ecological process.

210 Here we used a Multivariate ANOVA or Multivariate Analysis Of Variance (MANOVA) as it is able to capture
211 model differences based on the combined information of the multiple structural network measures. Model
212 defined as `network structure values ~ model + time period` and Linear Discriminant Analysis (LDA)
213 to determine if different models produced networks with differing structure.

Table 2: An informative caption about the different network properties

Label	Definition	Scale	Reference (for maths), can make footnotes probs
Connectance	L/S^2 , where S is the number of species and L the number of links	Macro	
GenSD	Normalized standard deviation of generality of a species standardized by L/S	Micro	Williams & Martinez (2000)
LinkSD	Normalized standard deviation of links (number of consumers plus resources per taxon)	Micro	
Richness	Number of nodes in the network	Macro	
TL	Prey-weighted trophic level averaged across taxa	Macro	Williams & Martinez (2004)
VulSD	Normalized standard deviation of vulnerability of a species standardized by L/S	Micro	Williams & Martinez (2000)

Label	Definition	Scale	Reference (for maths), can make footnotes probs
Diameter	Diameter can also be measured as the average of the distances between each pair of nodes in the network	Macro	Delmas et al. (2018)
ρ	Spectral radius is a conceptual analog to nestedness (and more appropriate for unipartite networks). It is defined as the absolute value of the largest real part of the eigenvalues of the <i>undirected</i> adjacency matrix	Macro	Staniczenko et al. (2013)
Complexity	SVD complexity of a network, defined as the Pielou entropy of its singular values	Macro	Strydom et al. (2021a)
S1	Number of linear chains	Meso	Milo et al. (2002); Stouffer et al. (2007)
S2	Number of omnivory motifs	Meso	Milo et al. (2002); Stouffer et al. (2007)
S4	Number of apparent competition motifs	Meso	Milo et al. (2002); Stouffer et al. (2007)
S5	Number of direct competition motifs	Meso	Milo et al. (2002); Stouffer et al. (2007)

214 **5.2.1 Macro network properties**

215 **Connectance** (Martinez, 1992) has been shown to be the feature of networks that underpin a series of other
216 properties and function (Strydom et al., 2021b) and so it is perhaps the most important structural attribute for
217 a model to be able to retrieve correctly. Additionally we consider the **complexity** of networks by calculating
218 their SVD entropy (this gives us an estimate of the physical as opposed to behavioural complexity of networks;
219 Strydom et al. (2021a)), we could also look at the rank/rank deficiency of networks which (theoretically)
220 represents the number fo unique interaction strategies in the network (Strydom et al., 2021a), which may be
221 specifically interesting in terms of looking at pre and post extinction but also as a way to unpack ‘functional
222 redundancy’ that some models may introduce.

223 **5.2.2 Meso network properties**

224 Motifs represent smaller subset of interactions between three species, and are argued to capture dynamics
225 that are likely to be ecologically relevant (Milo et al., 2002; Stouffer et al., 2007). Here we specifically look at
226 the number of **linear chains**, **omnivory**, **apparent competition**, and **direct competition** motifs. In
227 the broader context the ability of a model in being able to capture these smaller motifs will inform as to its
228 suitability of use understanding the more dynamic component of network ecology.

229 **5.2.3 Micro network properties**

230 The number of interactions established (**generality**) or received (**vulnerability**) by each species (Schoener,
231 1989), are (broadly) indicative of consumer-resource relationships and diet breadth of species [ref]. Although
232 this is usually determined at the species level the standard deviation of the generality and vulnerability of
233 species is often used when benchmarking predicted networks (Petchey et al., 2008; *e.g.*, Williams & Martinez,
234 2008).

235 The **specificity** of species in a network is measured as a function of the proportion of resources they effectively
236 use (Poisot et al., 2012)

237 [Figure 1 about here.]

238 And we can discuss the results and implications here...

239 **5.3 Assessing pairwise interaction differences**

240 **Interaction turnover** (Poisot et al., 2012) tells us which interactions are ‘conserved’ (shared) across the
241 networks from the same period but constructed using different models.

242

[Figure 2 about here.]

243 **5.4 Assessing network inference**

244 Here we will look at extinctions of the different paleo TSS Gupta et al. (2022)

245 **5.4.1 Robustness**

246 R_{50} see Jonsson et al. (2015)

247 [Figure 3 about here.]

248 **Discussion**

249 Blah blah blah

250 **References**

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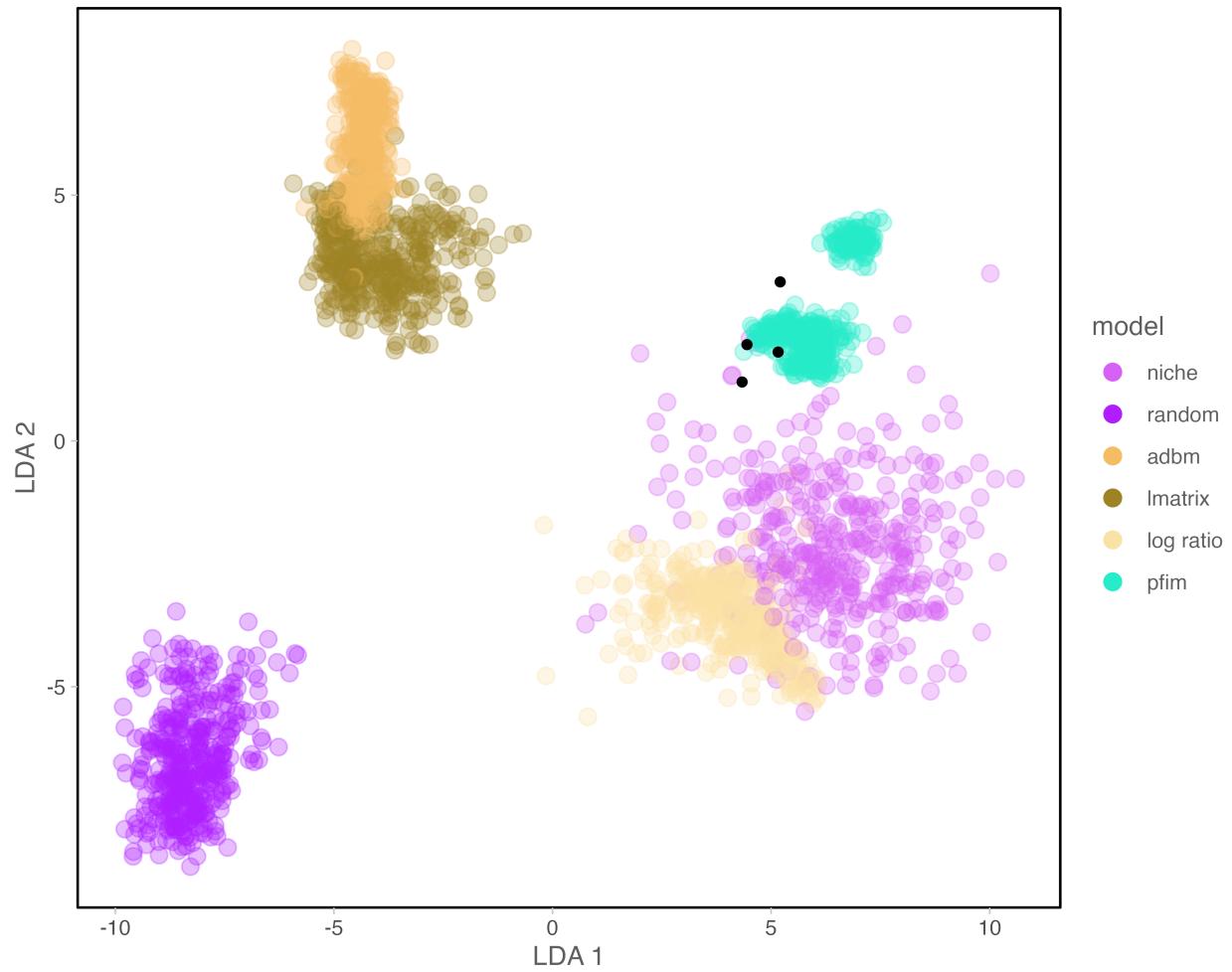


Figure 1: stuff...

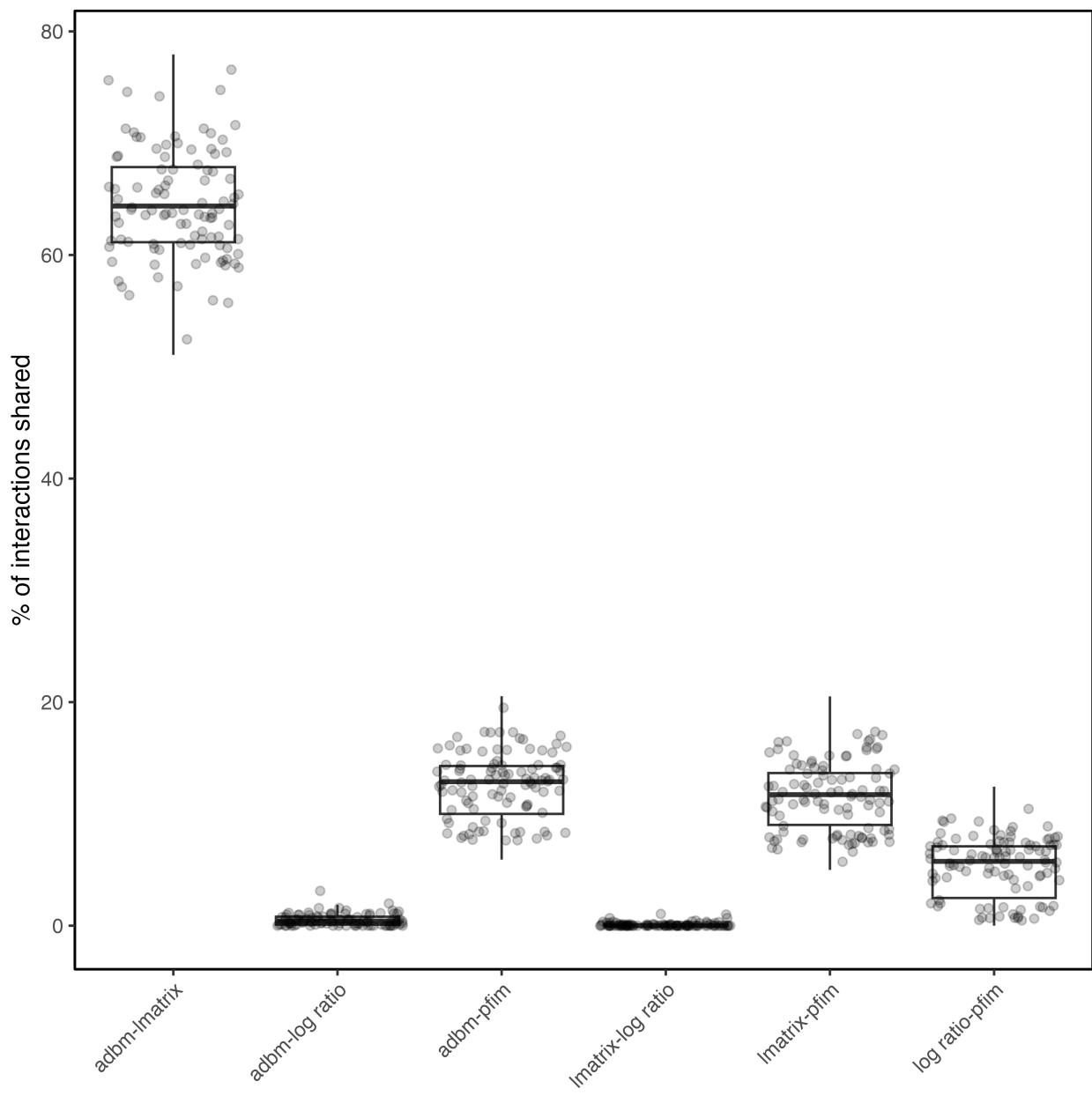


Figure 2: stuff... % interaction shared is calculated as number shared interactions / ((number interactions left - shared interactions) + (number interactions right - shared interactions) + shared interactions). Additionally niche and random models are excluded as it is illogical since both of these models are fundamentally species agnostic

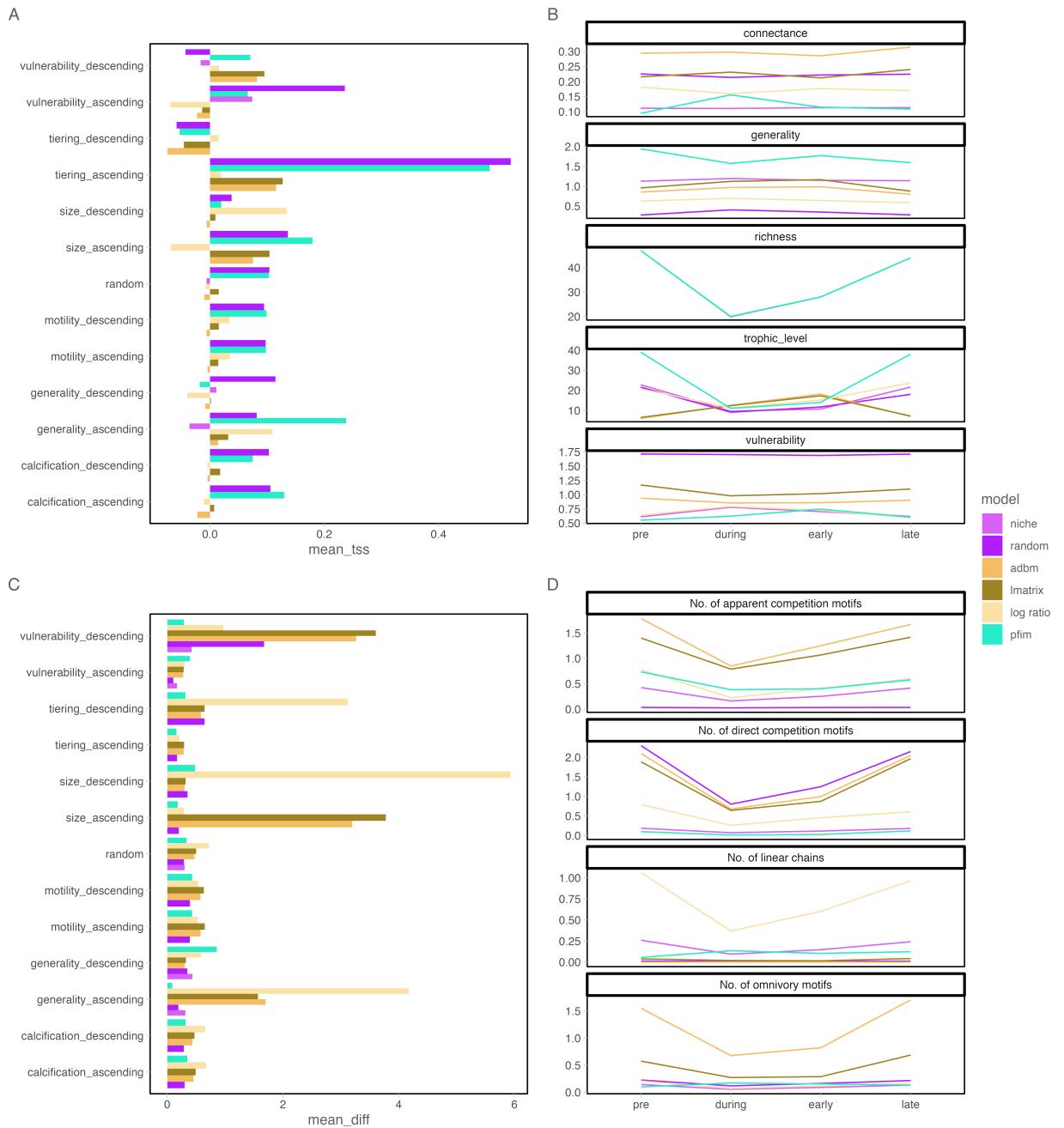


Figure 3: stuff... Recreation of the figure from Dunhill 2024. Note not 100% sold on the TSS and absolute mean calculations...