

# Methods for Reconstructing Paleo Food Webs

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**Abstract:** TODO.

**Keywords:** food web, network construction

<sub>1</sub> **1 Why build paleo food webs?**

- <sub>2</sub>     • Because its interesting?
- <sub>3</sub>     • Value in using hindcasting to aid in forecasting. *e.g.*, the Toarcian ms (Dunhill et al., 2024) shows how  
<sub>4</sub> we can use these paleo communities to understand trophic-level responses to extinctions.

<sub>5</sub> **2 How do we do it?**

- <sub>6</sub>     • There is an evolving body of work that focuses on developing tools specifically for the task of predicting  
<sub>7</sub> food webs.
- <sub>8</sub>     • There are a handful that have been developed specifically in the context of paleo settings *e.g.*, TODO  
<sub>9</sub> but we can also talk about those that might have been developed/tested in contemporary settings but  
<sub>10</sub> still have applicability in paleo ones.
- <sub>11</sub>    • Different underlying theory though
- <sub>12</sub>      – Focus here on the idea of different ‘currencies’ but also aggregations - energy vs compatibility.
- <sub>13</sub>    • Insert brief overview of the different methods as they pertain to approach (so the T4T triangle)
- <sub>14</sub>    • Challenges we face (even in contemporary settings)?
- <sub>15</sub>      – keep high level - I think the argument here should fall more in the data trade offs...

<sub>16</sub> **3 Understanding how networks are different**

<sub>17</sub> It is important to be aware that networks can be configured in different ways depending on how the inter-  
<sub>18</sub> actions are defined (Strydom, in prep). Basically we have metawebs, which represent *potential* interactions,  
<sub>19</sub> and realised networks, which represent the subset of potential that are realised as a result of community and  
<sub>20</sub> environmental context.

<sub>21</sub> **4 Challenges specific to paleo communities/networks**

<sub>22</sub> Although there are a suite of tools and methods that have been developed to predict species interactions and  
<sub>23</sub> networks they will not all be suitable for the prediction of paleo communities. Some of these include the fact  
<sub>24</sub> that the fossil record is incomplete/preservation is biased [REF] which means that we have an incomplete  
<sub>25</sub> picture of the entire community. Fossils are 2D and only represent specific ‘parts’ of an individual (hard and

<sup>26</sup> bone-y bits), this means we don't have a complete picture of the physical traits of species *e.g.*, no body mass  
<sup>27</sup> (but yes size), behaviours, or ability to construct well resolved phylogenetic trees the deeper we go back in  
<sup>28</sup> time. Also owing to the patchy nature of fossils one often has to aggregate over large spatial scales, and also  
<sup>29</sup> fossils are preserved in 2D so no *real* idea of spatial arrangements, compounded that fossils aren't necessarily  
<sup>30</sup> conserved/found 'in situ' but can be moved (*e.g.*, alluvial deposits). Methodologically speaking some tools  
<sup>31</sup> that 'learn' from contemporary communities (*e.g.*, Strydom et al. (2023), Caron et al. (2022)) will become  
<sup>32</sup> 'worse' the further one goes back in time since species then look very different from now but can still be  
<sup>33</sup> useful for 'recent' communities (*e.g.*, Fricke et al. (2022)). Something about the intersectionality of the data  
<sup>34</sup> we don't have for paleo communities and the data we need for some of the different modelling approaches.

## <sup>35</sup> 5 Dataset Overview

- <sup>36</sup> • Species  
<sup>37</sup> • Time/space  
<sup>38</sup> • And probably some other paleo things that will be relevant...

## <sup>39</sup> 6 Methods

### <sup>40</sup> 6.1 Models

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

Model	Predicts	Notes
Allometric diet breadth model	Realised network	
Body size ratio model	Metaweb (?)	
Niche model	Structural network	Is not species specific - cannot apply species metadata
Paleo food web inference model	Realised network (if downsampling)	

41 **6.1.1 Paleo food web inference model**

42 The Paleo food web inference model (PFIM; Shaw et al. (2024)) uses a series of rules for a set of trait  
43 categories (such as habitat and body size) to determine if an interaction can feasibly occur between a species  
44 pair. If all conditions are met for the different rule classes then an interaction is deemed to be feasible. The  
45 original work put forward in Shaw et al. (2024) also includes a ‘downsampling’ step developed by Roopnarine  
46 (2006) that uses a power law, defined by the link distribution, to ‘prune’ down some of the links. It is worth  
47 mentioning that this approach is similar to that developed by Roopnarine (2017) with the exception that  
48 Shaw does not specifically bin species into guilds, and so we choose to use the method developed by Shaw  
49 since both methods should produce extremely similar networks as they are built on the same underlying  
50 philosophy.

51 **6.1.1.1 Defining organism ecologies, feeding interactions and trophic guilds**

52 This is currently verbatim from the Dunhill ms...

53 Modes of life were defined for each fossil species based on the ecological traits defined in the Bambach  
54 ecospace model (Bambach et al., 2007). Ecological traits were assigned based on interpretations from the  
55 published literature which are largely based on functional morphology and information from extant relatives.  
56 Information on the body size of each species was also recorded by summarising mean specimen sizes from the  
57 section into a categorical classification. The following ecological characteristics were recorded for each fossil  
58 species; motility (fast, slow, facultative, non-motile), tiering (pelagic, erect, surficial, semi-infaunal, shallow  
59 infaunal, deep infaunal), feeding (predator, suspension feeder, deposit feeder, mining, grazer), and size:  
60 gigantic (>500 mm), very large (>300–500 mm), large (>100–300 mm), medium (>50–100 mm), small (>10–  
61 50 mm), tiny ( 10 mm). Size categories are defined by the longest axis of the fossil, estimates of tracemaker  
62 size from trace fossils based on literature accounts, or by extrapolating the total length for belemnites from  
63 the preserved guard using established approaches.

64 **6.1.2 Allometric diet breadth model**

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

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

69 where  $\lambda_{ij}$  is the handling time, which is the product of the attack rate  $A_i$  and resource density  $N_i$ ,  $E_i$  is the  
 70 energy content of the resource and  $H_{ij}$  is the ratio handling time, with the relationship being dependent on  
 71 the ratio of predator and prey body mass as follows:

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

72 or

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

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

#### 74 6.1.3 Body size ratio model

75 The body size ratio model (Rohr et al., 2010) determines feeding interactions using the ratio between consumer  
 76 and resource body sizes - which supposedly stems from niche theory (still trying to reconcile that myself).  
 77 The probability of a link existing between a consumer and resource (in its most basic form) is defined as  
 78 follows:

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

79 where

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

80 The original latent-trait model developed by Rohr et al. (2010) also included an additional latent trait term  
 81  $v_i \delta f_j$  however for simplicity we will use Equation 2 as per Yeakel et al. (2014) Based on Rohr et al. (2010) it  
 82 is possible to estimate the parameters  $\alpha$ ,  $\delta$ , and  $\gamma$  using a GLM but we will use the parameters from Yeakel  
 83 et al. (2014), which was ‘trained’ on the Serengeti food web data and are as follows:  $\alpha = 1.41$ ,  $\delta = 3.75$ , and  
 84  $\gamma = 1.87$ .

85 **6.1.4 Niche model**

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

93 **6.2 Assessing model performance**

94 In terms of wanting to asses and compare across the different models it is beneficial to approach this task  
95 by thinking about the different aspects of the network as well as interactions that are being predicted by the  
96 different models. It is perhaps beneficial to think of these across different ‘scales’ of organisation within the  
97 network, namely macro (the entire network), meso (smaller interacting units within the network), and micro  
98 (species-level attributes). Although there are a myriad of possible ways to ‘measure’ and analyse ecological  
99 networks (Delmas et al., 2018) we do still lack a clear set of guidelines for assessing how well models recover  
100 network structure (Allesina et al., 2008) and it is beneficial to use a small subset of metrics that can clearly  
101 be tied to broader aspects of network function or capturing a ecological process.

102 **6.2.1 Meta network properties**

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

111 **6.2.2 Meso network properties**

112 Motifs represent smaller subset of interactions between three species, and are argued to capture dynamics  
113 that are likely to be ecologically relevant (Milo et al., 2002; Stouffer et al., 2007). Here we specifically look

114 at the number of **linear chains**, **omnivory**, **apparent competition**, and **direct competition** motifs. In  
115 the broader context the ability of a model in being able to capture these smaller motifs will inform as to its  
116 suitability of use understanding the more dynamic component of network ecology.

117 **6.2.3 Micro network properties**

118 The number of interactions established (**generality**) or received (**vulnerability**) by each species (Schoener,  
119 1989), are (broadly) indicative of consumer-resource relationships and diet breadth of species [ref]. Although  
120 this is usually determined at the species level the standard deviation of the generality and vulnerability of  
121 species is often used when benchmarking predicted networks (Petchey et al., 2008; *e.g.*, Williams & Martinez,  
122 2008).

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

125 **Shape:** to determine if the ‘shape’ of the network is correct we are looking at the ratio of  
126 ‘top’:‘basal’ species (where ‘top’ species are those that have a vulnerability of 0 and ‘basal’ species  
127 have a generality of 0) as well as the distance to base from one of the top species (this will  
128 represent the shortest path but a large discrepancy between the real and predicted network would  
129 be indicative that the model is not predicting a similar ‘shape’). This will allow us to see if the  
130 models construct tall ‘pencil’ vs flat ‘pancake’ networks (Beckerman 2024, pers comms). A small  
131 (< 1) number will thus be indicative of a ‘bottom-heavy’ network and the opposite for larger  
132 numbers

133 **7 Results**

134 **7.1 Comparing predicted networks**

135 [Figure 1 about here.]

136 **7.2 Comparing inference**

137 **7.3 Extinctions**

138 [Figure 2 about here.]

139 [Figure 3 about here.]

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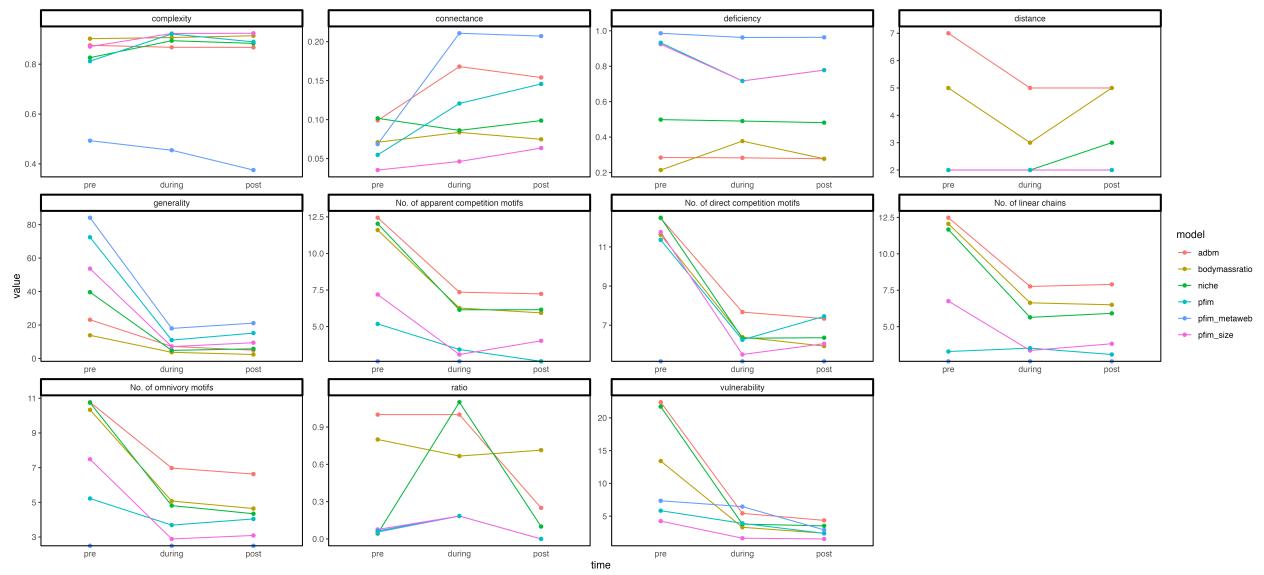


Figure 1: stuff... For display purposes the counts for the different motifs are log transformed

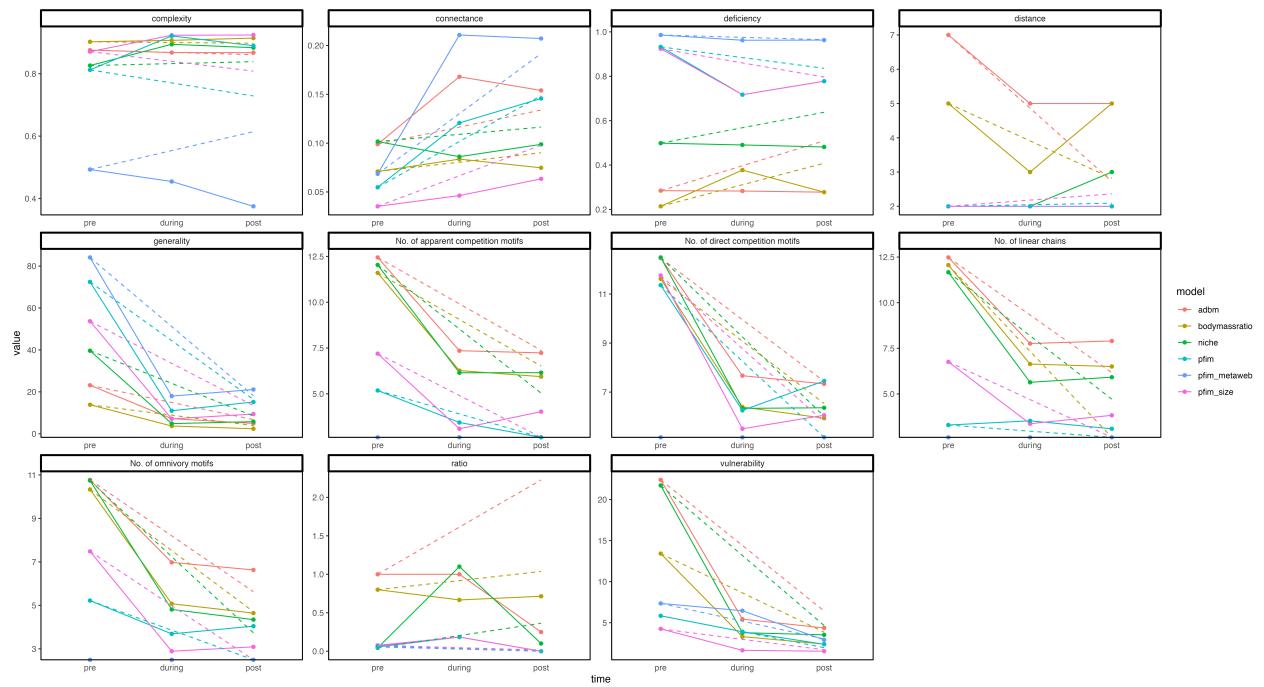


Figure 2: Dashed line indicates the (mean) extinction simulation results (post value, start values are those estimated by the relevant model). For display purposes the counts for the different motifs are log transformed

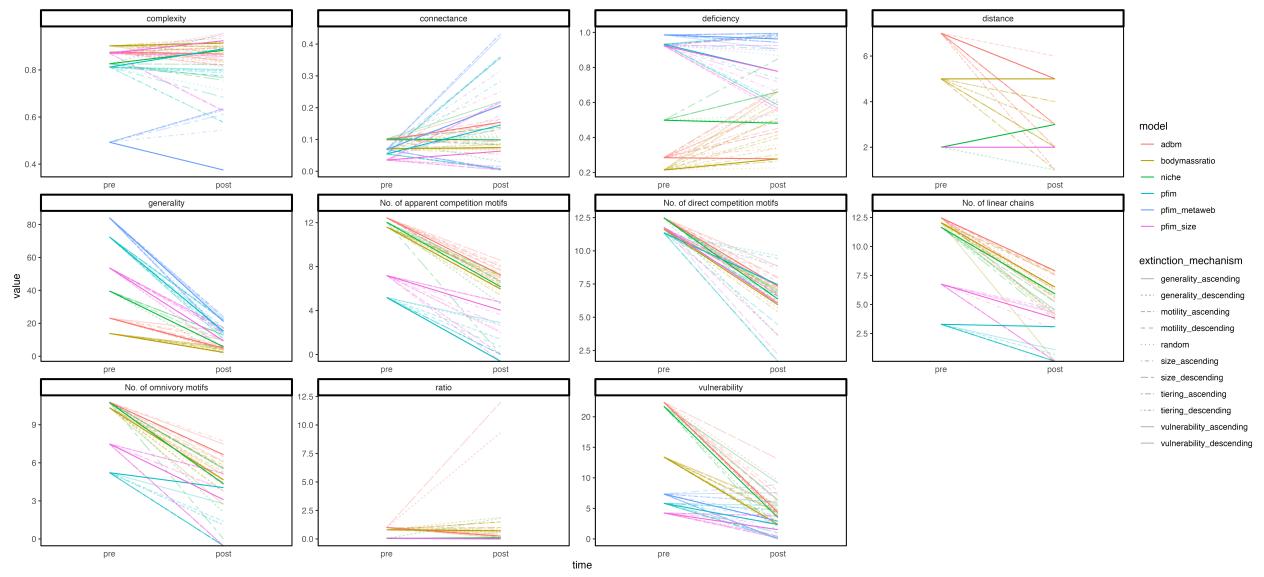


Figure 3: Dark line indicates ‘real’ extinction simulation results the lighter lines show each model individually, which is also denoted by the linetype. For display purposes the counts for the different motifs are log transformed