
SIMULTANEOUSLY ESTIMATING FOOD WEB CONNECTANCE AND STRUCTURE WITH UNCERTAINTY

A PREPRINT

Anubhav Gupta *

Department of Evolutionary Biology and Environmental Studies

University of Zurich

8057 Zurich, Switzerland

`anubhav.gupta@ieu.uzh.ch`

Reinhard Furrer

Department of Mathematics and Department of Computational Science

University of Zurich

8057 Zurich, Switzerland

`reinhard.furrer@math.uzh.ch`

Owen L. Petchey

Department of Evolutionary Biology and Environmental Studies

University of Zurich

8057 Zurich, Switzerland

`owen.petchey@ieu.uzh.ch`

November 21, 2021

Abstract

1) Food web models explain and predict the trophic interactions in a food web, and they can infer missing interactions among the organisms. The allometric diet breadth model (ADBM) is a food web model based on the foraging theory. In the ADBM the foraging parameters are allometrically scaled to body sizes of predators and prey. In Petchey et al. (2008), the parameterisation of the ADBM had two limitations: (a) the model parameters were point estimates, and (b) food web connectance was not estimated.

*Corresponding author

- 2) The novelty of our current approach is: (a) we consider multiple predictions from the ADBM by parameterising it with approximate Bayesian computation, to estimate parameter distributions and not point estimates. (b) Connectance emerges from the parameterisation, by measuring model fit using the true skill statistic, which takes into account prediction of both the presences and absences of links.
- 3) We fit the ADBM using approximate Bayesian computation to 12 observed food webs from a wide variety of ecosystems. Connectance was consistently overestimated in the new parameterisation method. In some of the food webs, considerable variation in estimated parameter distributions occurred, and resulted in considerable variation (i.e. uncertainty) in predicted food web structure.
- 4) These results lend weight to the possibility that the observed food web data is missing some trophic links that do actually occur. It also seems likely that the ADBM likely predicts some links that do not exist. The latter could be addressed by accounting in the ADBM for additional traits other than body size. Further work could also address the significance of uncertainty in parameter estimates for predicted food web responses to environmental change.

Keywords connectance · ABC · ADBM · food web · true skill statistic · uncertainty

1 Introduction

Knowledge about the trophic interactions among the organisms in a community is crucial for understanding the structure and dynamics of ecological communities and for predicting their response to environmental change (Dunne, Williams, and Martinez 2002; Tylianakis and Binzer 2014; O'Connor et al. 2009; Bergamino, Lercari, and Defeo 2011; Krause et al. 2003; Lurgi, L'opez, and Montoya 2012; Morris, Sinclair, and Burwell 2015). The network of trophic interactions is often referred to as a food web. The food web structure can provide answers to key ecological questions: which species are more vulnerable to environmental changes such as temperature (Owen L. Petchey et al. 1999); how robust a food web is to extinctions (Dunne, Williams, and Martinez 2002); and how a food web reacts if the predators are removed (Knight et al. 2005)?

Trophic interactions information from multiple sources can be used to infer a food web, e.g. gut contents (Peralta-Maraver, L'opez-Rodr'iguez, and de Figueroa 2016) and cannot be assigned with certainty to a specific prey item (Baker, Buckland, and Sheaves 2014). With stable isotope ratios of tissues, uncertainty may be due to factors such as variability in the isotopic fractionation values across multiple combinations of diets and tissues/species, unquantified temporal or spatial variation in prey isotopic values, and variation caused by routing of particular dietary nutrients into particular tissues (Crawford, McDonald, and Bearhop 2008). Furthermore, complete recording of all interactions usually requires a large sampling effort even at

small spatial and temporal scales (Hobson, Piatt, and Pitocchelli 1994). Food web structure is very difficult to record at larger spatial and temporal scales without losing resolution (spatial, temporal, and taxonomic) (Gravel et al. 2013; Martinez 1991; Jord'an and Osv'ath 2009). Less than complete sampling of interactions can result in no interaction being observed between a pair of individuals that in fact do interact, which results in missing links in a food web. Due to under-sampling, food webs can be poorly understood, which may hinder further advances in the field (Martinez et al. 1999).

When interactions are difficult to observe, and hence well-documented food webs are not available, models which predict species interactions may provide a solution (Tamaddoni-Nezhad et al. 2013; Gravel et al. 2013; Owen L. Petchey et al. 2008; Allesina, Alonso, and Pascual 2008a; Cohen, Newman, and Steele 1985). A food web model can be used to predict missing information about species interactions. For example, Owen L. Petchey et al. (2008) showed how a model of species interactions (and therefore food web structure) could be parameterised from data on the known presence and absence of trophic interactions. The model and its parameter values encode the rules for occurrence or absence of species interactions to predict food web structure. Observed data may be used to select and parameterise the model. Tamaddoni-Nezhad et al. (2013) used large agricultural datasets, logic-based machine learning and text mining to assign interactions between nodes to automatically construct food webs. Gravel et al. (2013), inspired by the niche model of food web structure developed a method that used the statistical relationship between predator and prey body size to infer the food web.

Food web models are also useful for ecological forecasting. Lindegren et al. (2010) used a stochastic food web model driven by regional climate scenarios to produce quantitative forecasts of cod dynamics in the twenty-first century. Hattab et al. (2016) forecasted the potential impacts of climate change on the local food web structure of the highly threatened Gulf of Gabes ecosystem, located in the south of the Mediterranean Sea. Hence, food web models have an important role in filling gaps in knowledge about species interactions, including predicting future changes in food web structure.

The allometric diet breadth model (ADBM) was the first model able to predict food web connectance and structure (Beckerman, Petchey, and Warren 2006; Owen L. Petchey et al. 2008). It uses foraging theory, specifically the contingency model (MacArthur and Pianka 1966), to predict the diet of each potential consumer and thereby the food web structure (further details are in the Material and Methods section). The ADBM had variable success in explaining the structure of 15 different food webs, with the proportion of links correctly predicted ranging from 5 % to 65 % (Table 1). The ADBM correctly predicted 65% of the presence of links in the Coachella valley food web. The poorest prediction of presence of links was for the Grasslands food web with only 7% of the presence of links correctly predicted. When trophic interactions were more strongly dependent on size, the model correctly predicted a greater proportion of links. Indeed, constructing a food web based only on body size (i.e. ignoring taxonomy) resulted in almost twice the number of correctly predicted links, i.e. 83%, in contrast to taxonomy (Woodward et al. 2010).

Although Owen L. Petchey et al. (2008) demonstrated that foraging theory could predict food web structure, their implementation of the ADBM included at least two limitations. The parameterisation method provided estimates of the parameters with no uncertainty: a single set of parameter values that maximised the explanatory power was selected. In other words, the parameterisation method led to point estimates of the parameters that predicted a single food web structure (because the ADBM is purely deterministic). Moreover, the best predicted food web was not exactly the same as the observed one. In a sense then, the parameterisation method used in Owen L. Petchey et al. (2008) was akin to estimating the intercept and slope of a regression line, but not any uncertainty in those parameters. Given that uncertainty is an essential dimension in ecological models, and in predictions about the future state of ecological communities (Owen L. Petchey et al. 2015; Carpenter 2016), this is an important limitation.

The second limitation was in the estimation of the connectance of the food web, which is the number of realised trophic links divided by the total number of possible trophic links. Although the ADBM can in principle predict connectance, Owen L. Petchey et al. (2008) prevented the model from doing so. They set the value of relevant parameters in the model to instead ensure the predicted connectance was equal to the observed connectance. The ADBM was not therefore used to simultaneously predict connectance and structure of food webs. Moreover, fixing predicted connectance to be equal to observed connectance does not account for the possibility that the observed connectance was imperfectly measured. Indeed, if low effort was used to observe the trophic links in a community, the observed connectance are likely to be lower than if all trophic links were observed. Connectance is an important driver for the stability and dynamics of a food web (May 1972) and most of the structural properties of food webs co-vary with connectance (Dunne, Williams, and Martinez 2002; Poisot and Gravel 2014), thus this limitation must be addressed.

In this article we report on how we address these limitations. We removed the first limitation by applying approximate Bayesian computation (ABC). The approach originated in population genetics and has been used in a wide range of research fields: systems biology (Toni et al. 2009), ecology (Jabot and Chave 2009), epidemiology (Shriner et al. 2006) and ecological networks (Ibanez 2012; Poisot and Stouffer 2016). One of the advantages of ABC is that it does not require a likelihood function. As ADBM is a complex deterministic model where the likelihood can not be explicitly evaluated, ABC is a good choice of parameterisation.

We addressed the second limitation by allowing estimation of number of links as well as arrangement of links. To accomplish this, we measured model fit by using the true skill statistic, which takes into account both the number of presences and absences of links correctly predicted. High values of the true skill statistic occurs when both the predicted arrangement of links and the predicted number of links are close to the observed arrangement and number of links, respectively.

Table 1: Information about the food webs predicted using the ADBM.

Common food web name (Original Publication)	Predation matrix source	Body size source	General ecosystem	Number of species	Connectance	Body size range (approximate)	Proportion of presence of links correct	Type of interactions
Benguela Pelagic (Yodzis 1998)	Brose et al. (2008)	Brose et al. (2008)	Marine	30	0.21	10^{-8} to 10^6	0.54	Predation
Broadstone Stream (taxonomic aggregation) (Woodward and Hildrew 2001; Woodward et al. 2005)	Brose et al. (2008)	Brose et al. (2008)	Freshwater	29	0.19	10^{-6} to 10^{-2}	0.40	Predation
Broom (Mommott et al. 2000)	Brose et al. (2008)	Brose et al. (2008)	Terrestrial	60	0.03	10^{-6} to 10^0	0.09	Herbivory, Parasitism, Predation, Pathogenic
Capinteria (Lafferty et al. 2006)	Hechinger et al. (2011)	Hechinger et al. (2011)	Marine (Salt Marsh)	88	0.08	10^{-6} to 10^4	0.33	Predator-parasite, Parasite-parasite
Caricaie Lakes (Cattin et al. 2004)	Brose et al. (2008)	Brose et al. (2008)	Freshwater	158	0.05	10^{-5} to 10^5	0.13	Predation, Parasitism
Grasslands (Dawah et al. 1995)	Brose et al. (2008)	Brose et al. (2008)	Terrestrial	65	0.03	10^{-3} to 10^{-2}	0.07	Herbivory, Parasitism
Mill Stream (Ledger, Edwards, Woodward unpublished)	Brose et al. (2008)	Brose et al. (2008)	Freshwater	80	0.06	10^{-6} to 10^{-2}	0.36	Herbivory, Predation
Skipwith Pond (Warren 1989)	Brose et al. (2008)	Brose et al. (2008)	Freshwater	71	0.07	10^{-4} to 10^{-1}	0.14	Predation
Small Reef (Opitz 1996 Table 8.6.2)	Alyssa R. Cirtwill and Anna Eklöf (2018)	Alyssa R. Cirtwill and Anna Eklöf (2018)	Marine (Reef)	239	0.06	10^{-11} to 10^5	0.30	Predation, Herbivory
Tuesday Lake (Jonsson et al. 2005)	Brose et al. (2008)	Brose et al. (2008)	Freshwater	73	0.08	10^{-11} to 10^3	0.46	Predation
Ythan (Emmerson and Raffaelli 2004)	Alyssa R. Cirtwill and Anna Eklöf (2018)	Alyssa R. Cirtwill and Anna Eklöf (2018)	Marine (Estuarine)	88	0.05	10^{-12} to 10^0	0.22	Predation
Broadstone Stream (size aggregation) (Woodward et al. 2010)	Guy Woodward. (2021)	Guy Woodward. (2021)	Freshwater	29	0.24	10^{-7} to 10^2	0.83	Predation

2 Materials and Methods

In the upcoming sections, we present a detailed account of the application of ABC to parameterise the ADBM, the description of the ADBM and of the food web data we used. We explain the rejection Monte Carlo ABC method in the main text, and Markov chain Monte Carlo ABC and sequential Monte Carlo ABC methods in the Supplementary information (hereafter SI) Section S1 (hereafter SI-S1). We computed an accuracy measure known as true skill statistic to assess the ADBM's predictions and calculated different food web properties to compare these predictions across food webs.

2.1 Allometric Diet Breadth Model (ADBM)

The allometric diet breadth model (ADBM) is based on optimal foraging theory, specifically the contingency foraging model (MacArthur and Pianka 1966). The ADBM predicts the set of prey species a consumer should feed upon to maximise its rate of energy intake (Owen L. Petchey et al. 2008) (hereafter referred as PBRW study). The species in this set are assumed to have the trophic link with the predator. To make these predictions, the model assumes that a foraging predator is in one of two exclusive states: searching for prey or handling a prey item. The model requires four variables for each potential predator-prey interaction:

- The energy content of the resources E_i (only prey i specific) (energy).
- The handling times H_{ij} , which is the time not spent searching caused by consuming a prey item (prey i and predator j specific) (time).
- The space clearance rates A_{ij} (also known as the attack rate; prey i and predator j specific) (area or volume per time).
- The prey densities N_i (only prey i specific) (individuals per area or volume).

The term “Allometric” in the ADBM refers to the use of four allometric relationships, one for each of these four variables, including the body size of the predator M_j and prey M_i (Table 2). With these four allometric relationships, and the body size of each of the species in a community, we can predict the four variables (energy, handling time, space clearance rate, and prey density), and then use the contingency foraging model to predict diets.

Table 2: Traits with their allometric function and corresponding parameters in ADBM.

Traits (Unit)	Allometric function	Parameters	Comments
Energy (<i>Joules</i>)	$E_i = eM_i$	e	Arbitrary. No effect on structure. See SI S4
Abundance (individual/ m^2 or individual/ m^3)	$N_i = nM_i^{n_i}$	n	Connectance affected by the product nah . See SI S4
		n_i	Assumed value of $\frac{-3}{4}$ based on empirical data
Space Clearance Rate (m^2/s or m^3/s)	$A_{ij} = aM_i^{a_i}M_j^{a_j}$	a	Connectance affected by the product nah . See SI S4
			Estimated using ABC
		a_i	Estimated using ABC
		a_j	Estimated using ABC
Handling time (s)	$H_{ij} = \frac{h}{b - \frac{M_i}{M_j}}$ if $\frac{M_i}{M_j} < b$	h	Connectance affected by the product nah . See SI S4
	$H_{ij} = \infty$ if $\frac{M_i}{M_j} \geq b$	b	Estimated using ABC

Each of the four allometric equations has parameters: a constant and/or at least one exponent (Table 2). It is the value of some of these parameters that can be estimated to have the predicted food web structure match (as closely as possible) the structure of an observed food web. This is akin to choosing values of slope and intercept of a linear regression that maximises the fit of the regression line to the observed data.

Because some of the allometric constants and exponents are known, and because others are redundant with respect to each other (see Table 2 for details), we estimate only the following parameters: a , a_i , a_j and b in the model (Table 2).

In the ADBM, some species can be predicted to eat others, but to not be eaten by others, i.e. be predicted to be a top predator. This can occur for relatively large species when the exponent b is less than 1, which can cause the handling time of this large species to be infinite for all potential consumer species.

2.2 Observed food web data

The observed food webs that we fit the ADBM to belong to marine, freshwater and terrestrial ecosystems (Table 1). The observed connectance of these food webs is from 0.02 to 0.34 and there are 19 to 158 species. The food webs contain primary producers, herbivores, carnivores, parasites, and parasitoids. They also contain various types of feeding interactions, including predation, herbivory, bacterivory, parasitism, pathogenic, and parasitoid.

The goodness of fit of the ADBM's predictions depends on the types of interactions in the food webs in the PBRW study. Because some of the interactions are more size structured than other

155 interactions. Predacious and aquatic herbivore interactions were predicted better than parasitoid
 156 and herbivory ones (PBRW study).

157 All food webs with one exception (Broadstone Stream) was available only at the species level,
 158 i.e. with information about interactions between species and the body size of species. We use the
 159 term “species” in this study to indicate a “node” in a food web in which nodes are connected by
 160 trophic interactions, and nodes are a collection of individuals that share links. These species/nodes
 161 are not always taxonomic species, but can be broader taxonomic ranks.

162 In contrast, the Broadstone Stream food web data contained interactions between individuals
 163 and the individual body sizes. Thus, the Broadstone Stream food web can be constructed by
 164 aggregating by either taxonomy or size (Woodward et al. 2010).

165 **2.3 Parameter estimation: Approximate Bayesian Computation**

166 We used approximate Bayesian computation (ABC) to identify sets of parameter values that resulted
 167 in predicted food webs that were close in structure to the observed food web. ABC is an approach
 168 that does not require a likelihood function. Instead, there is a distance function that measures the
 169 distance between a model’s prediction and the observed data. The approximation of the likelihood
 170 depends on the ABC method used, which is further discussed below and SI. The model parameter
 171 values are sampled from a prior distribution. The accepted parameter values form an approximate
 172 posterior distribution for the model parameter. We implemented three ABC methods to parameterise
 173 the ADBM: namely rejection Monte Carlo (Fig. 1), Markov chain Monte Carlo, and sequential
 174 Monte Carlo. The three methods produced very similar results (SI Figs S33-S34) and we therefore
 175 only include the simplest (rejection) in this main text.

176 **2.3.1 Prior distribution**

177 The prior distributions for a_i and a_j were chosen to be uniform distributions. The range of
 178 distribution was from -1.5 to 1.5 and 0 to 3 for a_i and a_j respectively, informed by the estimates in
 179 Rall et al. (2012). However, we chose a prior range specific to food webs for the parameter b because
 180 body size varies greatly among the species in the observed food webs. For example: in the Benguela
 181 Pelagic food web, the body sizes of species range from the order of 10^{-8} gm to 10^5 gm. Hence, the
 182 range of prey-predator ratio was from the order of 10^{-14} to 10^{14} . To take this into account, we took

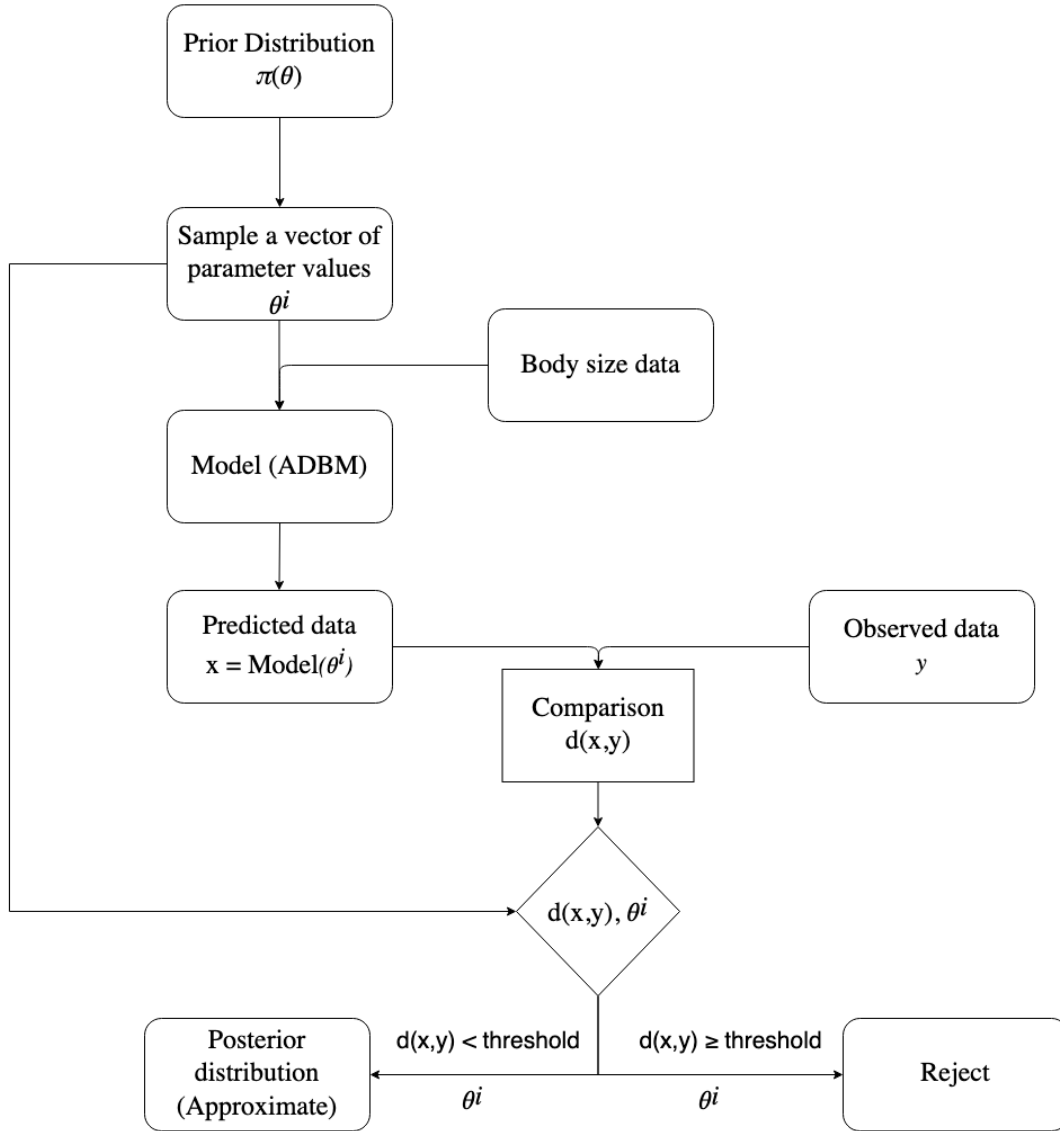


Figure 1: Flowchart of rejection approximate Bayesian computation method implemented to parameterise the ADBM.

the prior of $\log_{10}(b)$ from a uniform distribution ranging from -15 to 15 . In the case of parameter a , we chose the prior of $\log_{10}(a)$ to be a uniform distribution. However, the prior range varied between food webs. For example, the prior range for Benguela Pelagic was chosen to be -12 to 10 .

For the prior of a , we chose the prior of $\log_{10}(a)$ to be a uniform distribution. Since, the ADBM estimated connectance to be higher than the real connectance, lower values of a were favoured in the parameterisation. Hence, the upper bound of the prior was set to 10 . To set the lower bound, we investigated how the true skill statistic varied with $\log_{10}(a)$ (e.g. SI Fig. S35). We found that the TSS increased with decreasing $\log_{10}(a)$ and then remained constant, for a constant value of $\log_{10}(b)$. We therefore decided to set the lower bound of $\log_{10}(a)$ such that the maximum variation of TSS was taken into account, while attempting to keep the range of prior as small as possible. In the case of Benguela Pelagic as shown in SI Fig. S35, the lower bound of $\log_{10}(a)$ was taken to be -12 .

2.3.2 Comparison of observed and predicted

The difference between the model's prediction and the observed data (e.g. the sum of squared residuals is such a distance in linear regression) is quantified by a distance measure. The distance is lower when there is a closer match between the model's prediction and the observation. A perfect match would result in zero distance.

The magnitude of the distance is used for the acceptance or rejection of a set of parameter values. An accepted set of parameter values contributes to the posterior distribution, rejected ones do not. This makes the distance measure one of the important features of ABC. A threshold distance is chosen, and if the distance for a particular set of parameter values is less than the threshold, then that set of parameter values contributes to the posterior distribution. When the distance is greater than the threshold, the parameter values do not contribute to the posterior. Hence, the magnitude of the distance threshold determines the proportion of a model's parameters that are accepted. A higher threshold causes a high proportion of acceptances but less accuracy with the acceptance of some parameter sets that result in predictions quite unlike the observed data. Below, we first describe and justify our choice of distance measure, and then our choice of threshold.

Choice of distance measure In the PBRW study the measure of distance was equivalent to $1 - TP/(TP + FN)$, where TP is the number of observed links that were predicted (the number

of true positives) and FN is the number of observed links that were not predicted (the number of false negatives). A distance of 0 indicates that all observed links were correctly predicted. One way for the ADBM to achieve this is to predict that every species has a trophic link with every other species including itself – a fully connected food web with connectance of 1. The PBRW study prevented this by constraining the number of predicted links to be equal to the number of observed links, i.e. the model connectance was fixed to be the same as the observed connectance. In this study, we relaxed this constraint, with the number of links as well as the arrangement of links being estimated. The first step was to choose an appropriate distance measure.

The distance measure used in this study is 1 minus the true skill statistic: $\text{distance} = 1 - \text{TSS}$. This distance ranges from 0 to 2.

TSS is defined as:

$$\text{TSS} = \frac{TP \cdot TN - FP \cdot FN}{(TP + FN)(FP + TN)}$$

where TP is the number of observed links that are predicted by the model (true positives), TN is the number of observed absences of links that are correctly predicted (true negatives), FP is the number of false positives, and FN is the number of false negatives.

The TSS ranges from -1 to 1 , where $+1$ indicates a perfect prediction. A TSS value of zero or less indicates a performance no better than random.

The inclusion of true and false negatives in the distance measure means that the best theoretically possible prediction (smallest distance) is a unique prediction, and specifically the one in which the predicted presence and absence of links matches exactly with the observed presence and absence of links.

Choice of threshold value of distance Food web dynamics and stability are strongly dependent on connectance (May 1972), we therefore set the distance threshold (for acceptance) such that the model had a reasonable chance of predicting the observed value of connectance. Note that in the following section (*The Rejection ABC method*) we use the term *tol* to denote the value of the distance threshold.

236 To do this, we examined how the predicted connectance varied with the distance threshold.
 237 An example of this relationship is given in Fig. 2 for the Benguela Pelagic food web. We chose
 238 the minimum threshold value that gave a range of predicted connectance containing the observed
 239 connectance.

240 Furthermore, it is useful to note that in Fig. 2 there are no connectance values below a distance
 241 threshold value of less than 0.5 because for this particular food web there were no sets of parameter
 242 values that achieved a better model fit than is indicated by $1 - TSS = 0.5$. I.e. it is impossible for
 243 the ADBM to make better predictions than this. One reason for this is that the ADBM, when body
 244 size is the only trait, can only predict contiguous diets in trait space, whereas the observed data
 245 contains gaps in the diet.

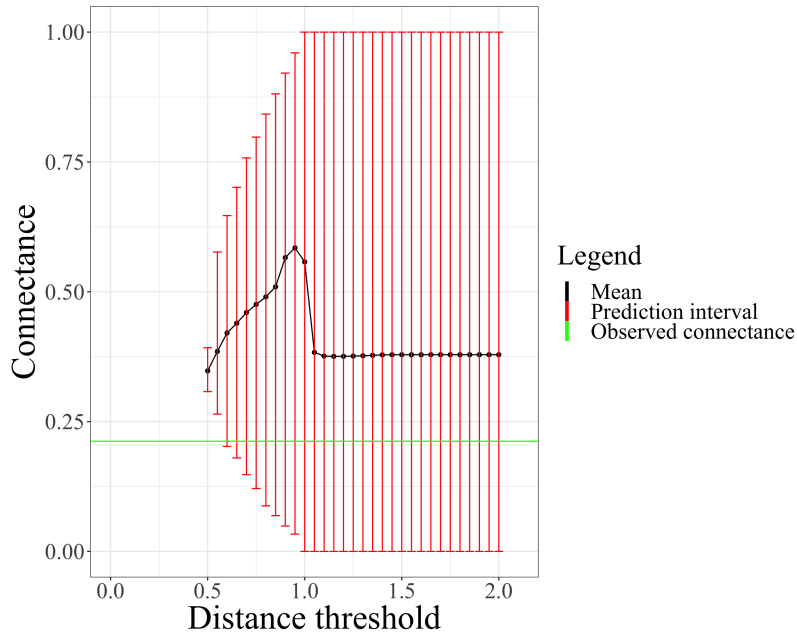


Figure 2: The prediction interval of the predicted connectance increases with increasing distance threshold for the Benguela Pelagic food web. The green line and black line represent the observed connectance and mean of predicted connectance respectively.

246 2.3.3 The Rejection ABC method

247 In the rejection ABC method, a set of parameter values are sampled from the prior distributions.
 248 This set of parameter values is either accepted, and thereby added to the posterior distribution of the

parameter values, or it is rejected (based on if the distance $1 - TSS$ is less than or greater than the threshold distance, as mentioned above). This process is repeated until there are enough acceptances to give stable (approximate) posterior distributions. In addition, we used a kernel function that assigns weight to each set of parameter values, where the weight is inversely proportional to the distance ($1 - TSS$).

In the upcoming section, we further detail the rejection ABC method.

Properties:

- A prior distribution $\pi(\theta)$: π is the uniform distribution for parameters $\theta = (a, a_i, a_j, b)$
- A model prediction $model(\theta)$: $ADBM(\theta)$. This is a predicted food web, x_i , given by a particular set of parameter values θ_i . Hence, $x_i = ADBM(\theta_i)$
- A summary statistic $s(x)$: x is the predation matrix predicted by the ADBM.
- A kernel function $K(u)$: epanechnikov $K(u) = \frac{1}{tol} \cdot \frac{3}{4} (1 - (\frac{u}{tol})^2)$ if $u \leq tol$
 $= 0$ otherwise

where tol is the distance threshold

- A distance function $d(x_i, y)$: $d(x_i, y) = 1 - TSS(x_i, y)$
- An observed food web y , in the form of a predation matrix containing zeros and ones.

Sampling:

for $i = 1 \dots n = 1000$

- Draw a set of parameter values θ_i from the prior distribution $\pi(\theta)$.
- Compute the model result $x_i = model(\theta_i)$
- Compute $s(x_i)$ and $d(s(x_i), s(y))$
- Accept or reject the parameter set probabilistically:
 - Assign a probability p_i to θ_i as per the kernel K ; $p_i = \frac{K(d)}{K(0)}$, where d is the distance evaluated in the previous step.
 - Compute $\alpha \sim U(0, 1)$

– If $\alpha \leq p_i$, then accept θ_i and $i = i + 1$

Output:

An approximate joint posterior distribution using the accepted $\theta_1, \dots, \theta_n$.

2.4 Assessment of model fit

Accuracy is how close the model prediction is to the observation. The ADBM's prediction is a predation matrix that consists of the presence and absence of links thus comparing how close the prediction is to the observation is not straightforward as comparing two numerical values. We defined the accuracy of the ADBM using true skill statistics to take into account the true and false predictions of both the presence and absence of links, which is defined above.

We examined how closely structural properties of the predicted food web matched those of the observed food webs using the R *cheddar* package (Hudson et al. 2013). We evaluated properties such as proportion of basal species, proportion of intermediate species, proportion of top species, proportion of herbivores, mean omnivory, clustering coefficient, standard deviation of generality, standard deviation of vulnerability, diet similarity, mean path length and nestedness. We could not compute mean trophic level and maximum trophic level because the networks had lot of paths which were too many to compute for the R *cheddar* package for all the food webs.

We investigated the performance of the ADBM parameterised with the ABC by computing standardised error of the food web properties, where the standardised error is the absolute raw error (the difference between observed and predicted value) divided by the maximum absolute raw error for that property. We did not calculate the standardised error for mean omnivory and mean path length because it had some NA values and infinite values for all the food webs respectively.

3 Results

As an example of the model outcomes, we first present the results for the Benguela food web (e.g. predicted food web structure, variation in predicted food web structure, and posterior parameter distributions). We chose this food web as it was well explained using the method of Petchey et al (2008) (hereafter referred as PBRW study). The results of the other food webs are included in

the SI Figs S1-S32. We then compare model outcomes across all empirical food webs between the PBRW study and our current work. We compare the true skill statistic of the two approaches and compare some food web properties, such as proportions of basal, intermediate, and top species.

The true skill statistic (TSS) of the predicted Benguela Pelagic food web varied between 0.4 and 0.52. This variation in the TSS is represented in terms of predation matrices displayed in Fig. 3(a), which overlays 1000 independent predation matrices accepted from the ABC method. In all the 1000 independent predation matrices, the predicted links are mostly present in the upper triangular portion of the matrix where most of the observed links are also present. Links in the upper right triangle of the predation matrix are for predators feeding on prey smaller than themselves.

In the 1000 predicted predation matrices, there predators are sometimes smaller than their predicted prey, the links in the lower left triangle of the predation matrix. This is also portrayed in the marginal distribution of $\log_{10}(b)$ in Fig. 4(d), as it includes values greater than $b = 2$ ($\log_{10}(b) = 0.3$). This is relevant as values of $b = 2$ make the most profitable prey item equal in size to the predator size. Lower values of b make the most profitable prey item smaller than the size of the predator.

There were around 250 potential links in the lower left triangle of the predation matrix that were never predicted in any of the 1000 predicted predation matrix (Fig. 3(b)). This strongly suggests that the predator-prey size ratio of these links is so small (i.e. very large prey, very small predator) that the links cannot occur, given that the preponderance of observed links are predators consuming prey smaller than themselves.

The marginal posterior of parameter b in the Benguela Pelagic food web was more constrained than the marginal posterior distribution of the other three allometric parameters (Fig. 4) as the posterior range was the narrowest.

The mean true skill statistic using the ABC approach was higher than the point estimates from the PBRW study (Fig. 5(a)) across all food webs except one. Our present approach led to estimates of connectance greater than the values of connectance of the PBRW study, which were fixed to equal the observed values of connectance.

We did not find a consistent relationship between the parameters estimated using the current approach and those estimated in the PBRW study (Fig. 5(c-f)), except for in the case of parameter

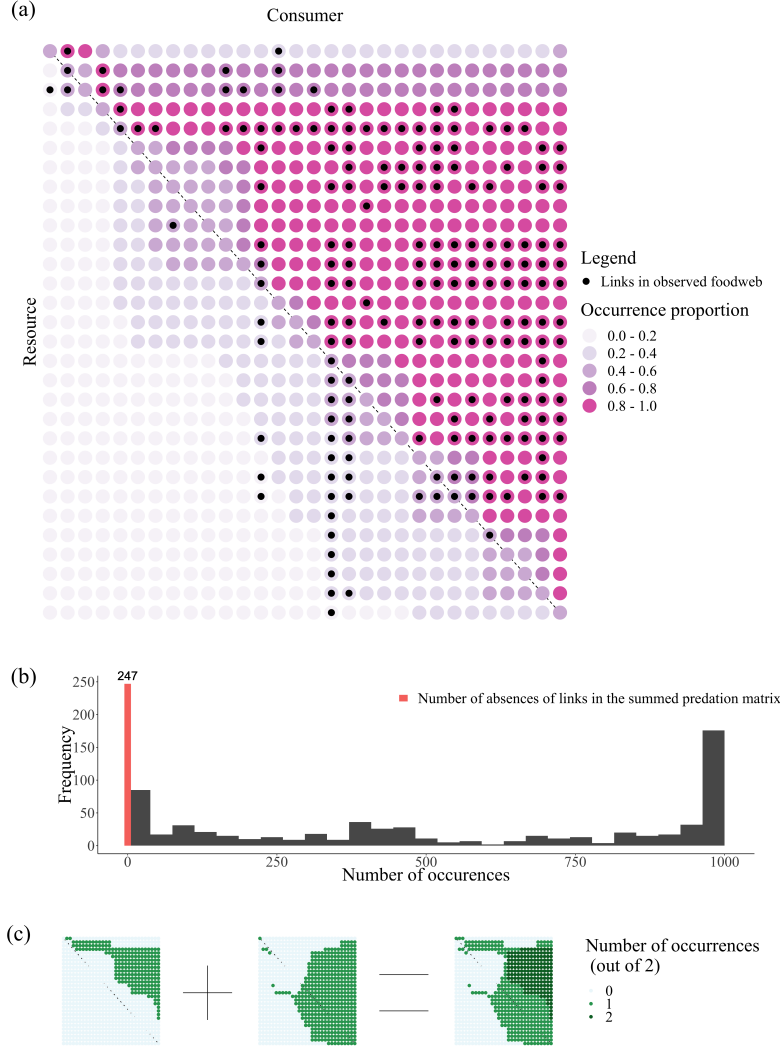


Figure 3: (a) Observed and predicted predation matrices for Benguela Pelagic food web. Body size increases from left to right and top to bottom along the predation matrix. Black circles show where there is an observed trophic link. The intensity of the pink circles shows the proportion of 1000 predicted food webs that had a trophic link between the corresponding species. This type of overlay is shown for two examples predicted in panel (c). (b) The histogram of the number of times a link was predicted across 1000 independently predicted food webs. There were 841 species pairs in this food web. About 150 of these were predicted to have a trophic link in all 1000 predicted predation matrices. The red bar shows the number of pairs of species for which a trophic link was never predicted. (c) Two predicted predation matrices for Benguela Pelagic food web corresponding to the minimum and the maximum value of estimated b , and their sum.

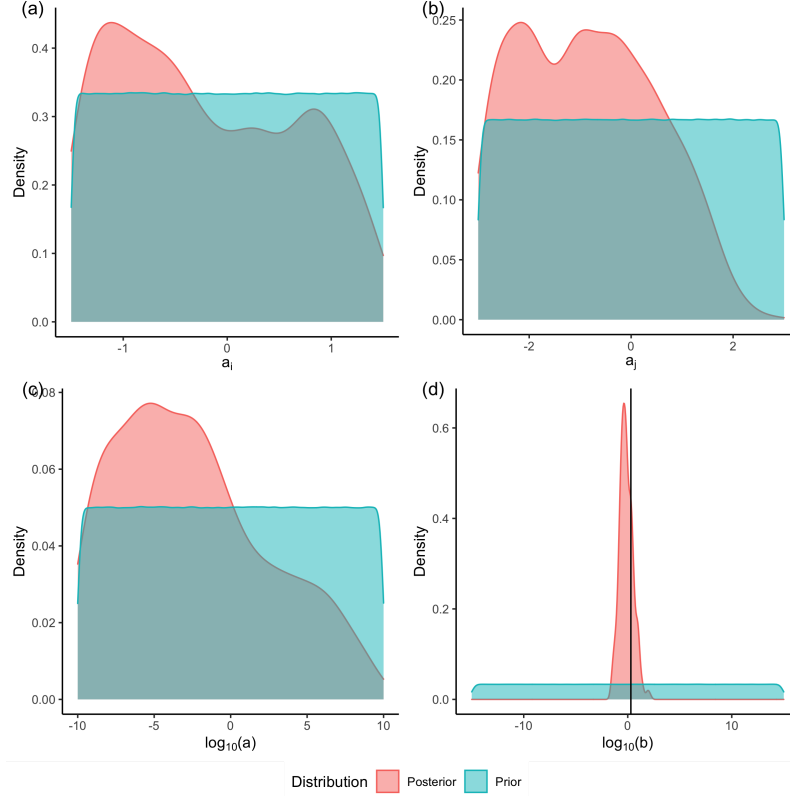


Figure 4: Marginal prior and marginal posterior distribution of the ADBM parameters for the Benguela Pelagic food web estimated using rejection ABC. The black vertical line in (d) corresponds to the value of b ($=2$) above which the most profitable prey item is larger in respect to the predator size.

328 b . The mean using the ABC approach was always higher than the estimates from the PBRW study
 329 (Fig. 5(f)) and the 95% credible interval of the posterior of b includes the estimate from the PBRW
 330 study.

331 The marginal posterior of parameter b was more constrained than the other three allometric
 332 parameters, i.e. the posterior range was the narrowest (SI Figs S17-S32). In most of the food webs,
 333 the parameter b had a unimodal distribution (SI Figs S17-S32). EcoWEB60 and Grasslands had a
 334 bimodal distribution and Sierra Lakes had three modes.

335 The structural food web properties proportion of intermediate species, mean omnivory, cluster-
 336 ing coefficient, sd of generality, sd of vulnerability, diet similarity and nestedness estimated from the

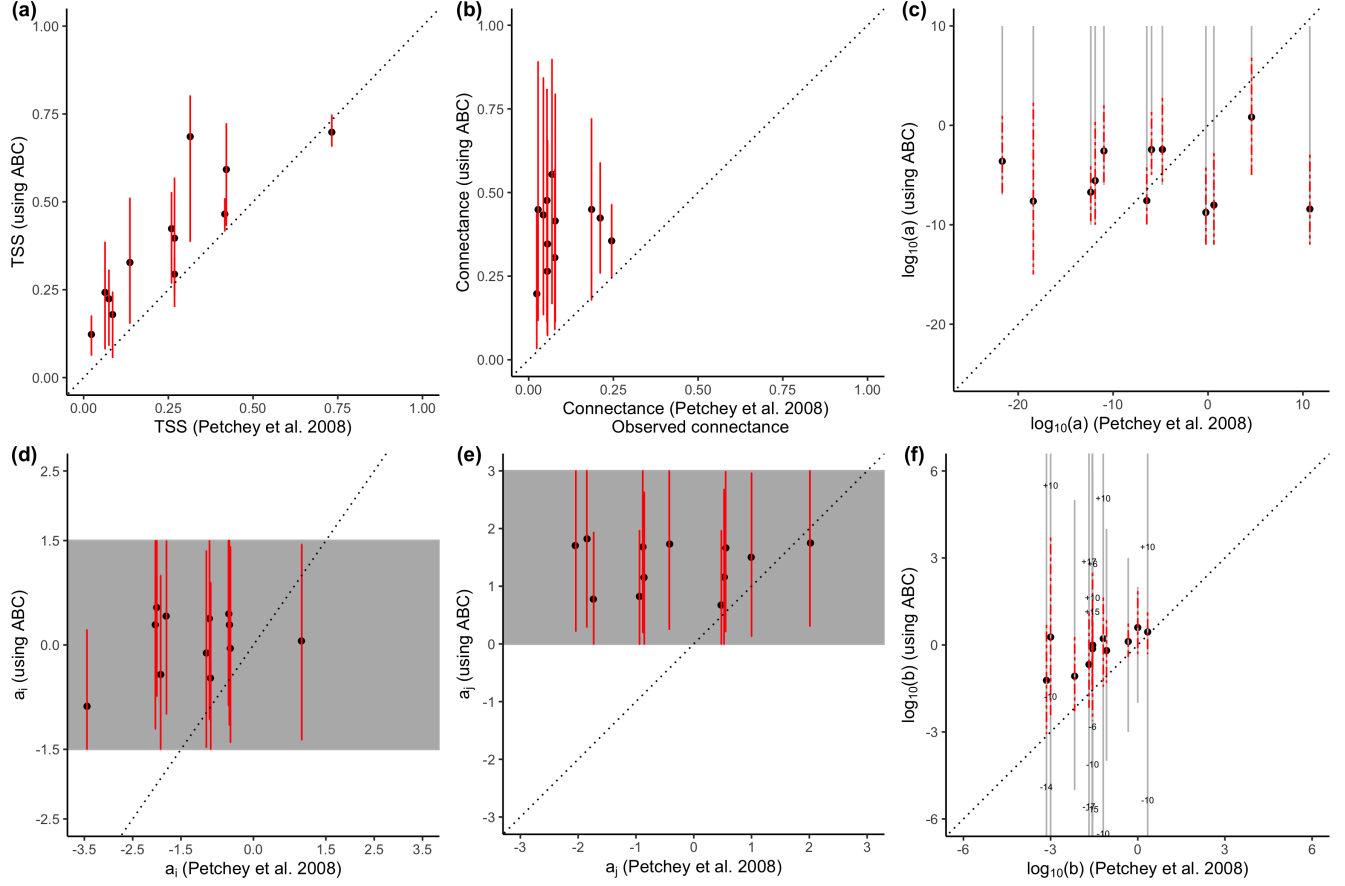


Figure 5: TSS (a), connectance (b) and ADBM parameters (c, d, e, f) computed using the ABC method compared with the corresponding point estimates from Petchev et al (2008). The red lines are the 95% credible/prediction intervals and the black filled circles represent the corresponding means. The grey region represents the intervals of the prior distributions for a_i and a_j . The grey lines represent the prior range of the parameters a and b in the \log_{10} scale. The prior range for the parameter b extends above and below the y-axis limits for some food webs and so the values of the limits are shown on the plot. The dashed black lines are the 1:1 relationships for reference.

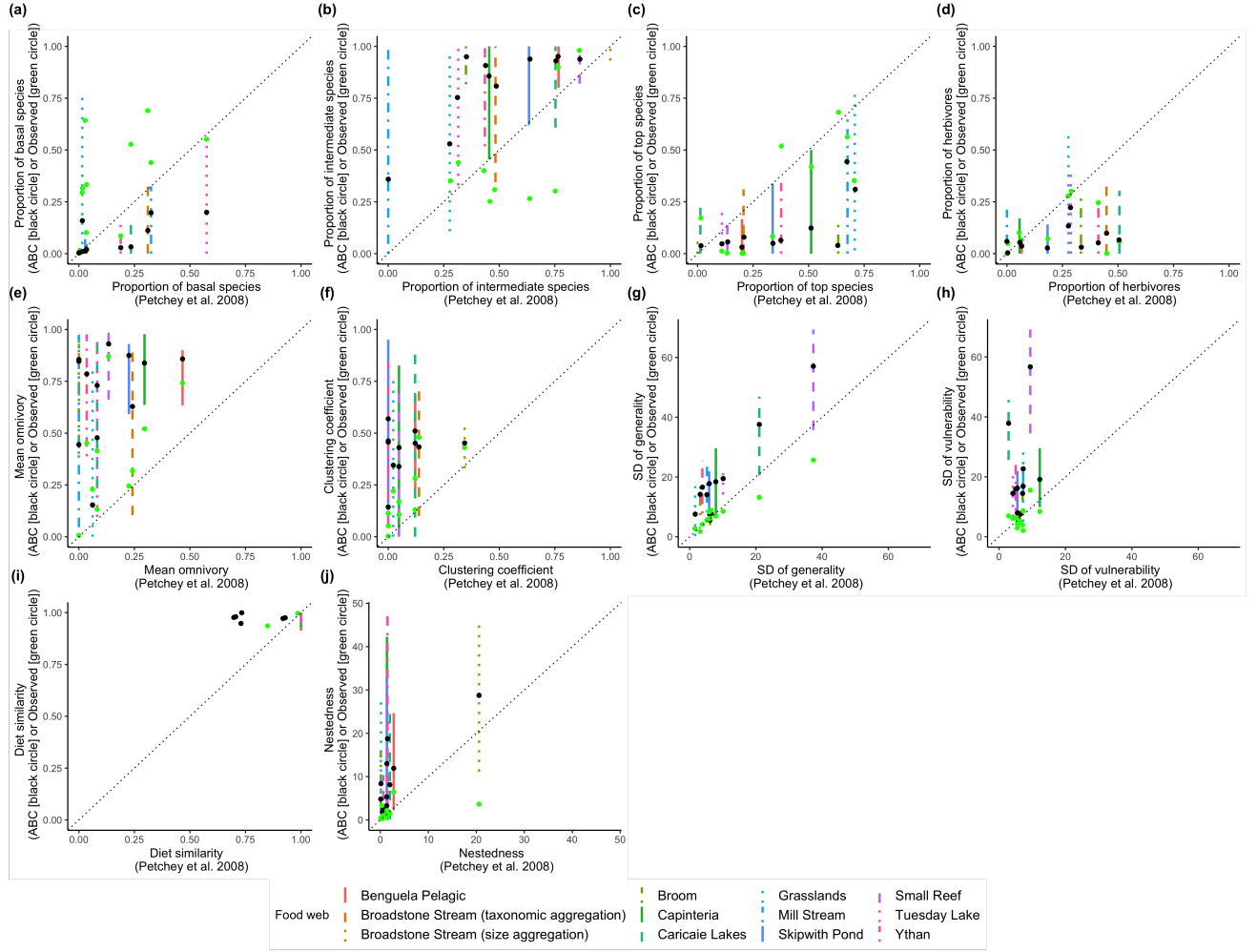


Figure 6: Structural properties of predicted food webs with 95% prediction interval parameterised using the ABC method plotted against the point estimates from Petchey et al. (2008). The black filled circles correspond to the mean, and green filled circles correspond to the properties of the observed food webs. The dashed black lines are the 1:1 relationships for reference.

current ABC approach were generally higher than the PBRW study (Fig. 6(b, e-j)). The properties proportion of basal species, proportion of top species, and proportion of herbivores were generally lower (Fig. 6(a, c, d)).

The real values of the proportion of intermediate species, mean omnivory, clustering coefficient, sd of generality, sd of vulnerability and nestedness, were mostly within the lower range of the

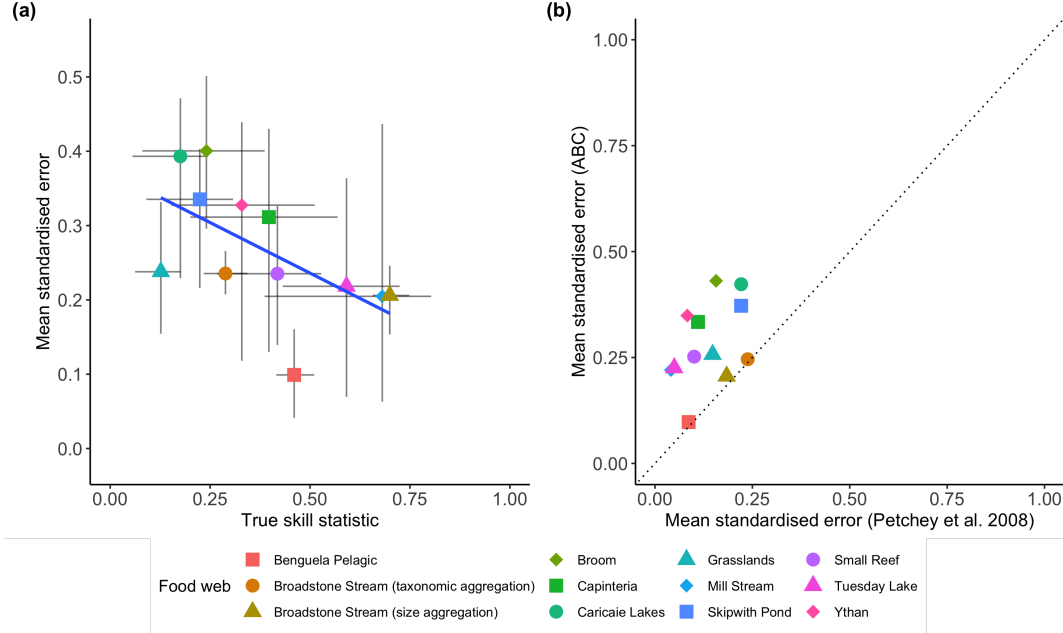


Figure 7: (a) The mean standardised error of the food web properties predicted from the ADBM parameterised using rejection ABC plotted against the mean true skill statistic for each food webs. The vertical and horizontal bars correspond to 95% prediction intervals of the standardised error and true skill statistic respectively. Solid blue line is linear regression through the means ($t = -2.335$, $df = 10$, $P = 0.041$). (b) The mean standardised error computed from the ABC method plotted against the mean standardised error from Petchey et al. (2008). The dashed line is the 1:1 relationship for reference.

342 predicted 95% interval. The proportion of basal species, proportion of top species, proportion of
 343 herbivores were underestimated in comparison to the real values for most of the food webs.

344 The ADBM, when parameterised with the ABC, generally better predicted the structural food
 345 web properties, such as proportion of basal species when the true skill statistics was higher (Fig.
 346 7(a)) across the 12 food webs. However, the ABC parameterised ADBM less accurately predicted
 347 food web properties on average than in the PBRW study (Fig. 7(b)).

348 Within each food web, we found various relationships between the standardised error and true
 349 skill statistic (SI Figs S37 and S38). E.g. For Skipwith Pond food web (SI Fig. S37(1)), high values
 350 of TSS were associated with high error, whereas the opposite was true for other food webs, such as
 351 Broadstone Stream (SI Fig. S37(b, p)). The other food webs showed more complex relationships.

352 4 Discussion

353 The ABC parameterisation method employed here improves on the basic parameterisation methods
 354 applied in Owen L. Petchey et al. (2008) (PBRW). The ABC method provides uncertainty in
 355 parameter estimates, and thereby a range of predicted food webs (Fig. 5(c-f)). It also allowed us to
 356 estimate parameters that were fixed by the PBRW study, and thereby also predicts connectance
 357 (Fig. 5(b)). Including uncertainty and predicting connectance are significant advances in ADBM.
 358 They allow predictions in changes of food web structure caused by environmental changes that
 359 include uncertainty in the predicted food web structure and including uncertainty in such predictions
 360 is critical (Owen L. Petchey et al. 2015; Cressie et al. 2009; Lindegren et al. 2010). A future
 361 development will be to partition the contribution of different sources of uncertainty such as incomplete
 362 sampling and model deficiencies to make improvements in the model with the aim of reducing
 363 uncertainty. Future research should investigate the functional and dynamical significance of the
 364 uncertainty in the predicted food web structure. Below we discuss some of the results of our study,
 365 and expand on these opportunities and priorities for future research.

366 In all cases, the predicted connectance was greater than the observed connectance (Fig. 5(b)).
 367 Why did this occur? Firstly, it is important to recognise that the ADBM (when using only body size
 368 as a trait) can only predict diets that are contiguous with respect to the size of prey. I.e. it cannot
 369 predict that a predator will consume prey of size 1 and 3, and not prey of size 2. Such patterns
 370 can however be predicted if a trait other than size and which is not perfectly correlated with size,
 371 influences foraging parameters (Owen L. Petchey et al. 2008; Allesina, Alonso, and Pascual 2008b;
 372 Williams and Martinez 2000). Secondly, it is important to note that the observed diets were not
 373 contiguous when prey are ordered by their size. The estimation process will result in a greater
 374 number of predicted links than observed given these features, and the model attempts to maximise
 375 the coincidence of predicted and observed link presence and absence (i.e. the true skill statistic).

376 These findings raise the question as to whether the model or the observed data is incorrect.
 377 We expect that the observed data does not contain some links that would occur in reality. This
 378 can be possible due to low sampling effort causing some links that do occur to be not observed.
 379 In this case, the model may correctly predict a link that was not yet observed as the data was
 380 incorrect. More intensive and more complete sampling of links in food webs has been recognised as

important, due to the potential that a low sampling effort will influence the perceived food web structure (Martinez et al. 1999).

We expect there are cases where the model incorrectly predicts a feeding link despite no possibility that such a link would occur in reality. This may be the case when a trait other than, or in addition to, prey size is influential. For example, a particular prey species may have a defensive trait that means it takes longer to consume it than an undefended prey of the same size. Incorporating traits other than body size in the ADBM would allow for discontinuous diets along the size axis. It is also possible that better estimate of parameters that could result from acquisition of new empirical data, could cause lower estimated values of connectance. Furthermore, the ADBM's current form is a biology-only model; it does not include an observation process, although this could be included. The model would then be able to predict the absence of a link due to incomplete observations.

It would be interesting to take a very well sampled food web (real or simulated) and remove links at random to create a less well sampled version, and to test if the very well sampled version can be predicted from the less well sampled version (with ABC parameter estimation). If it could, then there is potential to compensate for under-sampling with an appropriate food web model and estimation procedure.

The ABC parameterisation resulted in a lower prediction accuracy of structural features of the food webs (Fig. 7 (b)) due to the overestimation of connectance. This was confirmed by principal component analysis of variation in the food web structural properties which revealed a first PC axis representing on average 62% of the overall variance, and this first axis was highly correlated with connectance, with an average Spearman correlation of 0.87 (see SI S7 for details).

Our parameterisation approach was to maximise the true skill statistic (the coincidence of predicted and observed link presences, and the coincidence of predicted and observed link absences). The TSS assigns equal importance to the collection of presence and absence of observed links with the weight of an observed single presence or absence link being dependent on the connectance of the food web. If the connectance is less than 0.5, the TSS assigns more weight to a presence of link than to an absence of a link and vice versa.

409 Because the connectance of the observed food webs is less than 0.5 (Table 1), the TSS implicitly
 410 assigned more weight to a presence of link than to an absence of link. This upweighting of link
 411 presences seems appropriate since observing a feeding interaction is unambiguous, whereas not
 412 observing one may be caused by various processes. That is to say, the observation of a single feeding
 413 interaction is sufficient to record the presence of a link, whereas this is not true for the absence
 414 of links: one observation of a predator not consuming a prey does not mean that it will never do
 415 so. Nevertheless, if we observe no interaction between two species during the sampling period, we
 416 conclude that there is an absence of link.

417 To improve our estimation procedure we could quantify the uncertainty in the recorded absence
 418 of links and include this uncertainty in the parameterisation method. Weight/importance could
 419 be assigned to true positives, true negatives, false positives and false negatives calculated from
 420 empirical studies which may be specific to that food web. Alternatively, an observation process
 421 could be added to the model, such that the biological part of the model can predict that a feeding
 422 link is possible, but then the observation process in the model leads to that link not being predicted.

423 In the PBRW study, the parameter b played a major role in maintaining the maximum
 424 predictive power of the ADBM. Indeed, they found that estimating b only, and not estimating either
 425 a_i or a_j slightly decreased model performance, and that estimating only b and a_j did not decrease
 426 model performance relative to when all three parameters were estimated.

427 We found that the posterior distribution of the parameter b was the most constrained of all
 428 the parameters (Fig. 4). Parameter b defines the range of prey body size which has a finite handling
 429 time, and the prey size with the highest energetic profitability. As the parameter b relates to the
 430 prey-predator body size ratio, the constrained posterior of b (Fig. 4(d)) indicates the importance of
 431 the ratio of body size of prey and predator in determining the food web structure with the ADBM.

432 The marginal posterior of parameter a was right-skewed (Fig. 4(c)). This may be because
 433 the ABC parameterisation overestimates the connectance, which means that lower values of a are
 434 preferred over higher values of a (a lower value of a leads to a lower space clearance/attack rate,
 435 and a lower space clearance rate results in a higher connectance).

436 Information about who eats whom can be collected from multiple sources, such as gut contents
 437 of organisms, stable isotope composition of tissues, and experimentation (Peralta-Maraver, L'opez-

Rodríguez, and de Figueroa 2017; Layman et al. 2007; Warren 1989). Moreover, experimentation provides independent estimates of allometric foraging parameters, such as b , a_i , and a_j (Rall et al. 2012). Diverse data could be used to parameterise the ADBM’s predictions to test how uncertainty in the different datasets influences the ADBM’s predictions using ABC. Appropriate summary statistics in the ABC method could be used to address such challenges. We could use, as an example, the approximate trophic position inferred from stable isotope ratio data from an individual tissue and gut content data of a predator simultaneously to parameterise the ADBM. The trophic position and the gut content information would be the summary statistics in this example. A further question that could be addressed in future studies is how the quantity of data affects the ADBM’s predictions. The outcome of such a study could help food web researchers decide on how much data from a specific source is needed to predict the food web structure, and help further optimise the deployment of limited sampling resources.

When only partial food web data is available (Patonai and Jord’an 2017), the summary statistics in ABC can be used to infer these food web structures from the ADBM. It would be possible to use gut content data of only some of the species in a food web to parameterise the ADBM and predict the food web structure. Summary statistics opens up a broad spectrum of possibilities in parameterising food web models. There are multiple empirical and theoretical studies on a range of different food web properties of food webs across different ecosystems (Williams and Martinez 2000; Goldwasser and Roughgarden 1993; Martinez 1991). These can conceivably be used in parameterising food web models using ABC to constrain the model predictions.

5 Acknowledgements

This work was supported by the University Research Priority Program Global Change and Biodiversity (Grant number: U-704-04-11) of the University of Zurich. We thank the Petchey group members for their valuable suggestions in the manuscript. We thank Debra Zuppingner-Dingley for proofreading the manuscript.

463 6 Author contributions

464 Anubhav Gupta: Conceptualization (equal), formal analysis (lead), methodology (lead), software
 465 (lead), writing – original draft preparation (lead), writing - review and editing (equal). Owen L.
 466 Petchey: Conceptualization (equal), funding acquisition (lead), methodology (supporting), resources
 467 (lead), writing – original draft preparation (supporting), writing - review and editing (equal).

468 7 Data Accessibility Statement

469 All the data used in this study was collected in other studies. We list those studies in Table 1. Some
 470 of those studies provide open access to their data and others do not. We have permission to use the
 471 data but do not have permission to distribute it.

472 References

- 473 Allesina, Stefano, David Alonso, and Mercedes Pascual. 2008a. “A General Model for Food Web
 474 Structure.” *Science* 320 (5876): 658–61. <https://doi.org/10.1126/science.1156269>.
- 475 ———. 2008b. “A General Model for Food Web Structure.” *Science* 320 (5876): 658–61. <https://doi.org/10.1126/science.1156269>.
- 477 Baker, Ronald, Amanda Buckland, and Marcus Sheaves. 2014. “Fish Gut Content Analysis: Robust
 478 Measures of Diet Composition.” *Fish and Fisheries* 15 (1): 170–77. <https://doi.org/10.1111/faf.12026>.
- 480 Beckerman, A. P., O. L. Petchey, and P. H. Warren. 2006. “Foraging Biology Predicts Food Web
 481 Complexity.” *Proceedings of the National Academy of Sciences of the United States of America*
 482 103: 13745–49. [://000240648300036](https://doi.org/10.1073/pnas.0608137103).
- 483 Bergamino, Leandro, Diego Lercari, and Omar Defeo. 2011. “Food Web Structure of Sandy Beaches:
 484 Temporal and Spatial Variation Using Stable Isotope Analysis.” *Estuarine, Coastal and Shelf
 485 Science* 91 (4): 536–43. <https://doi.org/10.1016/j.ecss.2010.12.007>.

- 486 Brose, Ulrich, Lara Cushing, Eric L. Berlow, Tomas Jonsson, Carolin Banasek-Richter, Louis-Felix
 487 Bersier, Julia L. Blanchard, et al. 2005. "Body Sizes of Consumers and Their Resources." *Ecology*
 488 86 (9): 2545–45. <https://doi.org/10.1890/05-0379>.
- 489 Carpenter, Stephen R. 2016. "Ecological Futures: Building an Ecology of the Long Now." *Ecology*,
 490 October, 2069–83. [https://doi.org/10.1890/0012-9658\(2002\)083%5B2069:EFBAE0%5D2.0.](https://doi.org/10.1890/0012-9658(2002)083%5B2069:EFBAE0%5D2.0.CO;2@10.1002/(ISSN)1939-9170.MacArthurAward)
 491 CO;2@10.1002/(ISSN)1939-9170.MacArthurAward.
- 492 Cattin, Marie-France, Louis-F'elix Bersier, Carolin Banašek-Richter, Richard Baltensperger, and
 493 Jean-Pierre Gabriel. 2004. "Phylogenetic Constraints and Adaptation Explain Food-Web
 494 Structure." *Nature* 427 (6977, 6977): 835–39. <https://doi.org/10.1038/nature02327>.
- 495 Cohen, Joel E. 1989. "Just Proportions in Food Webs." *Nature* 341 (6238, 6238): 104–5. <https://doi.org/10.1038/341104b0>.
- 497 Cohen, Joel E., C. M. Newman, and John Hyslop Steele. 1985. "A Stochastic Theory of Community
 498 Food Webs I. Models and Aggregated Data." *Proceedings of the Royal Society of London. Series*
 499 *B. Biological Sciences* 224 (1237): 421–48. <https://doi.org/10.1098/rspb.1985.0042>.
- 500 Crawford, Kerry, Robbie A. McDonald, and Stuart Bearhop. 2008. "Applications of Stable
 501 Isotope Techniques to the Ecology of Mammals." *Mammal Review* 38 (1): 87–107. <https://doi.org/10.1111/j.1365-2907.2008.00120.x>.
- 503 Cressie, Noel, Catherine A. Calder, James S. Clark, Jay M. Ver Hoef, and Christopher K. Wikle.
 504 2009. "Accounting for Uncertainty in Ecological Analysis: The Strengths and Limitations of
 505 Hierarchical Statistical Modeling." *Ecological Applications* 19 (3): 553–70. <https://doi.org/10.1890/07-0744.1>.
- 507 Dawah, Hassan Ali, Bradford A. Hawkins, and Michael F. Claridge. 1995. "Structure of the
 508 Parasitoid Communities of Grass-Feeding Chalcid Wasps." *The Journal of Animal Ecology* 64
 509 (6): 708. <https://doi.org/10.2307/5850>.
- 510 Dunne, Jennifer A., Richard J. Williams, and Neo D. Martinez. 2002. "Network Structure and
 511 Biodiversity Loss in Food Webs: Robustness Increases with Connectance." *Ecology Letters* 5 (4):
 512 558–67.

- 513 Emmerson, Mark C., and Dave Raffaelli. 2004. “Predator–Prey Body Size, Interaction Strength
514 and the Stability of a Real Food Web.” *Journal of Animal Ecology* 73 (3): 399–409. <https://doi.org/10.1111/j.0021-8790.2004.00818.x>.
515
- 516 Goldwasser, Lloyd, and Jonathan Roughgarden. 1993. “Construction and Analysis of a Large
517 Caribbean Food Web: Ecological Archives E074-001.” *Ecology* 74 (4): 1216–33. <https://doi.org/10.2307/1940492>.
518
- 519 Gravel, Dominique, Timoth’ee Poisot, Camille Albouy, Laure Velez, and David Mouillot. 2013.
520 “Inferring Food Web Structure from Predator-Prey Body Size Relationships.” Edited by Robert
521 Freckleton. *Methods in Ecology and Evolution* 4 (11): 1083–90. [https://doi.org/10.1111/](https://doi.org/10.1111/2041-210X.12103)
522 2041-210X.12103.
- 523 Harper-Smith, Sarah, Eric L. Berlow, Roland A. Knapp, Richard J. Williams, and Neo D. Martinez.
524 2005. “COMMUNICATING ECOLOGY THROUGH FOOD WEBS: VISUALIZING AND
525 QUANTIFYING THE EFFECTS OF STOCKING ALPINE LAKES WITH TROUT.” In *Dy-*
526 *namic Food Webs*, 407–23. Elsevier. <https://doi.org/10.1016/B978-012088458-2/50038-2>.
- 527 Hattab, Tarek, Fabien Leprieur, Frida Ben Rais Lasram, Dominique Gravel, François Le Loc’h,
528 and Camille Albouy. 2016. “Forecasting Fine-Scale Changes in the Food-Web Structure of
529 Coastal Marine Communities Under Climate Change.” *Ecography* 39 (12): 1227–37. <https://doi.org/10.1111/ecog.01937>.
530
- 531 Hobson, Keith A., John F. Piatt, and Jay Pitocchelli. 1994. “Using Stable Isotopes to Determine
532 Seabird Trophic Relationships.” *Journal of Animal Ecology* 63 (4): 786–98. [https://doi.org/](https://doi.org/10.2307/5256)
533 10.2307/5256.
- 534 Hudson, Lawrence N., Rob Emerson, Gareth B. Jenkins, Katrin Layer, Mark E. Ledger, Doris E.
535 Pichler, Murray S. A. Thompson, Eoin J. O’Gorman, Guy Woodward, and Daniel C. Reuman.
536 2013. “Cheddar: Analysis and Visualisation of Ecological Communities in R.” *Methods in Ecology*
537 *and Evolution* 4 (1): 99–104. <https://doi.org/10.1111/2041-210X.12005>.
- 538 Ibanez, S’ebastien. 2012. “Optimizing Size Thresholds in a Plant–Pollinator Interaction Web:
539 Towards a Mechanistic Understanding of Ecological Networks.” *Oecologia* 170 (1): 233–42.
540 <https://doi.org/10.1007/s00442-012-2290-3>.

- 541 Jabot, Franck, and J'érôme Chave. 2009. "Inferring the Parameters of the Neutral Theory of
542 Biodiversity Using Phylogenetic Information and Implications for Tropical Forests." *Ecology*
543 *Letters* 12 (3): 239–48. <https://doi.org/10.1111/j.1461-0248.2008.01280.x>.
- 544 Jonsson, Tomas. 1998. "Food Webs and the Distribution of Body Sizes."
- 545 Jonsson, Tomas, Joel E. Cohen, and Stephen R. Carpenter. 2005. "Food Webs, Body Size, and
546 Species Abundance in Ecological Community Description." In *Advances in Ecological Research*,
547 36:1–84. Elsevier. [https://doi.org/10.1016/S0065-2504\(05\)36001-6](https://doi.org/10.1016/S0065-2504(05)36001-6).
- 548 Jord'an, Ferenc, and Györgyi Osv'ath. 2009. "The Sensitivity of Food Web Topology to Temporal
549 Data Aggregation." *Ecological Modelling* 220 (22): 3141–46. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.ecolmodel.2009.05.002)
550 [ecolmodel.2009.05.002](https://doi.org/10.1016/j.ecolmodel.2009.05.002).
- 551 Knight, Tiffany M., Michael W. McCoy, Jonathan M. Chase, Krista A. McCoy, and Robert D.
552 Holt. 2005. "Trophic Cascades Across Ecosystems." *Nature* 437 (7060): 880–83. [https:](https://doi.org/10.1038/nature03962)
553 [//doi.org/10.1038/nature03962](https://doi.org/10.1038/nature03962).
- 554 Krause, Ann E., Kenneth A. Frank, Doran M. Mason, Robert E. Ulanowicz, and William W.
555 Taylor. 2003. "Compartments Revealed in Food-Web Structure." *Nature* 426 (6964): 282–85.
556 <https://doi.org/10.1038/nature02115>.
- 557 Lafferty, K. D., A. P. Dobson, and A. M. Kuris. 2006. "Parasites Dominate Food Web Links."
558 *Proceedings of the National Academy of Sciences* 103 (30): 11211–16. [https://doi.org/10.](https://doi.org/10.1073/pnas.0604755103)
559 [1073/pnas.0604755103](https://doi.org/10.1073/pnas.0604755103).
- 560 Layman, Craig A., D. Albrey Arrington, Carmen G. Montaña, and David M. Post. 2007. "Can
561 Stable Isotope Ratios Provide for Community-Wide Measures of Trophic Structure?" *Ecology* 88
562 (1): 42–48. [https://doi.org/10.1890/0012-9658\(2007\)88%5B42:CSIRPF%5D2.0.CO;2](https://doi.org/10.1890/0012-9658(2007)88%5B42:CSIRPF%5D2.0.CO;2).
- 563 Lindegren, Martin, Christian Möllmann, Anders Nielsen, Keith Brander, Brian R. MacKenzie,
564 and Nils Chr. Stenseth. 2010. "Ecological Forecasting Under Climate Change: The Case
565 of Baltic Cod." *Proceedings of the Royal Society B: Biological Sciences* 277 (1691): 2121–30.
566 <https://doi.org/10.1098/rspb.2010.0353>.
- 567 Lurgi, Miguel, Bernat C. L'opez, and Jos'e M. Montoya. 2012. "Climate Change Impacts on Body
568 Size and Food Web Structure on Mountain Ecosystems." *Philosophical Transactions of the Royal*

- 569 *Society B: Biological Sciences* 367 (1605): 3050–57. [https://doi.org/10.1098/rstb.2012.](https://doi.org/10.1098/rstb.2012.0239)
570 0239.
- 571 MacArthur, Robert H., and Eric R. Pianka. 1966. “On Optimal Use of a Patchy Environment.” *The*
572 *American Naturalist* 100 (916): 603–9.
- 573 Martinez, Neo D. 1991. “Artifacts or Attributes? Effects of Resolution on the Little Rock Lake
574 Food Web.” *Ecological Monographs* 61 (4): 367–92. <https://doi.org/10.2307/2937047>.
- 575 Martinez, Neo D., Bradford A. Hawkins, Hassan Ali Dawah, and Brian P. Feifarek. 1999. “Effects
576 of Sampling Effort on Characterization of Food-Web Structure.” *Ecology* 80 (3): 1044–55.
577 [https://doi.org/10.1890/0012-9658\(1999\)080%5B1044:E0SE0C%5D2.0.CO;2](https://doi.org/10.1890/0012-9658(1999)080%5B1044:E0SE0C%5D2.0.CO;2).
- 578 May, Robert M. 1972. “Will a Large Complex System Be Stable?” *Nature* 238 (5364): 413.
579 <https://doi.org/10.1038/238413a0>.
- 580 Memmott, J., N. D. Martinez, and J. E. Cohen. 2000. “Predators, Parasitoids and Pathogens:
581 Species Richness, Trophic Generality and Body Sizes in a Natural Food Web.” *Journal of Animal*
582 *Ecology* 69 (1): 1–15. <https://doi.org/10.1046/j.1365-2656.2000.00367.x>.
- 583 Morris, Rebecca J., Frazer H. Sinclair, and Chris J. Burwell. 2015. “Food Web Structure Changes
584 with Elevation but Not Rainforest Stratum.” *Ecography* 38 (8): 792–802. [https://doi.org/10.](https://doi.org/10.1111/ecog.01078)
585 1111/ecog.01078.
- 586 O’Connor, Mary I., Michael F. Piehler, Dina M. Leech, Andrea Anton, and John F. Bruno. 2009.
587 “Warming and Resource Availability Shift Food Web Structure and Metabolism.” Edited by Michel
588 Loreau. *PLoS Biology* 7 (8): e1000178. <https://doi.org/10.1371/journal.pbio.1000178>.
- 589 Opitz, Silvia. 1996. “Quantitative Models of Trophic Interactions in Caribbean Coral Reefs.”
- 590 Patonai, Katalin, and Ferenc Jord’an. 2017. “Aggregation of Incomplete Food Web Data May Help
591 to Suggest Sampling Strategies.” *Ecological Modelling* 352 (May): 77–89. [https://doi.org/10.](https://doi.org/10.1016/j.ecolmodel.2017.02.024)
592 1016/j.ecolmodel.2017.02.024.
- 593 Peralta-Maraver, I., M. J. L’opez-Rodr’iguez, and J. M. Tierno de Figueroa. 2016. “Structure,
594 Dynamics and Stability of a Mediterranean River Food Web.” *Marine and Freshwater Research*
595 68 (3): 484–95. <https://doi.org/10.1071/MF15154>.

- 596 Peralta-Maraver, I., M. J. L'opez-Rodríguez, and J. M. Tierno de Figueroa. 2017. "Structure,
597 Dynamics and Stability of a Mediterranean River Food Web." *Marine and Freshwater Research*
598 68 (3): 484–95. <https://doi.org/10.1071/MF15154>.
- 599 Petchey, Owen L., P. Timon McPhearson, Timothy M. Casey, and Peter J. Morin. 1999. "Envi-
600 ronmental Warming Alters Food-Web Structure and Ecosystem Function." *Nature* 402 (6757):
601 69–72. <https://doi.org/10.1038/47023>.
- 602 Petchey, Owen L., Mikael Pontarp, Thomas M. Massie, Sonia K'efi, Arpat Ozgul, Maja Weilenmann,
603 Gian Marco Palamara, et al. 2015. "The Ecological Forecast Horizon, and Examples of Its Uses
604 and Determinants." *Ecology Letters* 18 (7): 597–611. <https://doi.org/10.1111/ele.12443>.
- 605 Petchey, Owen L., Andrew P Beckerman, Jens O Riede, and Philip H Warren. 2008. "Size, Foraging,
606 and Food Web Structure." *Proceedings of the National Academy of Sciences* 105 (11): 4191–96.
- 607 Poisot, Timoth'ee, and Dominique Gravel. 2014. "When Is an Ecological Network Complex?
608 Connectance Drives Degree Distribution and Emerging Network Properties." *PeerJ* 2 (February):
609 e251. <https://doi.org/10.7717/peerj.251>.
- 610 Poisot, Timoth'ee, and Daniel B. Stouffer. 2016. "How Ecological Networks Evolve." Preprint.
611 Ecology. <https://doi.org/10.1101/071993>.
- 612 Polis, Gary A. 1991. "Complex Trophic Interactions in Deserts: An Empirical Critique of Food-Web
613 Theory." *The American Naturalist* 138 (1): 123–55. <http://www.jstor.org/stable/2462536>.
- 614 Rall, B. C., U. Brose, M. Hartvig, G. Kalinkat, F. Schwarzmuller, O. Vucic-Pestic, and O. L.
615 Petchey. 2012. "Universal Temperature and Body-Mass Scaling of Feeding Rates." *Philosophical*
616 *Transactions of the Royal Society B: Biological Sciences* 367 (1605): 2923–34. <https://doi.org/10.1098/rstb.2012.0242>.
- 618 Shriner, Daniel, Yi Liu, David C. Nickle, and James I. Mullins. 2006. "Evolution of Intrahost
619 Hiv - 1 Genetic Diversity During Chronic Infection." *Evolution* 60 (6): 1165–76. <https://doi.org/10.1111/j.0014-3820.2006.tb01195.x>.
- 621 Tamaddoni-Nezhad, Alireza, Ghazal Afroozi Milani, Alan Raybould, Stephen Muggleton, and David
622 A. Bohan. 2013. "Construction and Validation of Food Webs Using Logic-Based Machine

- Learning and Text Mining.” In *Advances in Ecological Research*, 49:225–89. Elsevier. <https://doi.org/10.1016/B978-0-12-420002-9.00004-4>.
- Toni, Tina, David Welch, Natalja Strelkowa, Andreas Ipsen, and Michael P. H. Stumpf. 2009. “Approximate Bayesian Computation Scheme for Parameter Inference and Model Selection in Dynamical Systems.” *Journal of the Royal Society Interface* 6 (31): 187–202. <https://doi.org/10.1098/rsif.2008.0172>.
- Tylianakis, Jason M., and Amrei Binzer. 2014. “Effects of Global Environmental Changes on Parasitoid-host Food Webs and Biological Control.” *Biological Control* 75 (August): 77–86. <https://doi.org/10.1016/j.biocontrol.2013.10.003>.
- Warren, Philip H. 1989. “Spatial and Temporal Variation in the Structure of a Freshwater Food Web.” *Oikos* 55 (3): 299. <https://doi.org/10.2307/3565588>.
- Williams, Richard J., and Neo D. Martinez. 2000. “Simple Rules Yield Complex Food Webs.” *Nature* 404 (6774, 6774): 180–83. <https://doi.org/10.1038/35004572>.
- Woodward, Guy, Julia Blanchard, Rasmus B. Lauridsen, Francois K. Edwards, J. Iwan Jones, David Figueroa, Philip H. Warren, and Owen L. Petchey. 2010. “Chapter 6 - Individual-Based Food Webs: Species Identity, Body Size and Sampling Effects.” In *Advances in Ecological Research*, edited by Guy Woodward, 43:211–66. Integrative Ecology: From Molecules to Ecosystems. Academic Press. <https://doi.org/10.1016/B978-0-12-385005-8.00006-X>.
- Woodward, Guy, and Alan G. Hildrew. 2001. “Invasion of a Stream Food Web by a New Top Predator.” *Journal of Animal Ecology* 70 (2): 273–88. <https://doi.org/10.1111/j.1365-2656.2001.00497.x>.
- Woodward, Guy, Dougie C. Speirs, and Alan G. Hildrew. 2005. “Quantification and Resolution of a Complex, Size-Structured Food Web.” In *Advances in Ecological Research*, 36:85–135. Elsevier. [https://doi.org/10.1016/S0065-2504\(05\)36002-8](https://doi.org/10.1016/S0065-2504(05)36002-8).
- Yodzis, Peter. 1998. “Local Trophodynamics and the Interaction of Marine Mammals and Fisheries in the Benguela Ecosystem.” *Journal of Animal Ecology* 67 (4): 635–58. <https://doi.org/10.1046/j.1365-2656.1998.00224.x>.