# Compensation masks trophic cascades in complex food webs

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#### Abstract

Ecological networks, or food webs, describe the feeding relationships between interacting species within an ecosystem. Understanding how the complexity of these networks influences their response to changing top-down control is a central challenge in ecology. Here, we provide a model-based investigation of trophic cascades — an oft-studied ecological phenomenon that occurs when changes in the biomass of top predators indirectly effect changes in the biomass of primary producers — in complex food webs that are representative of the structure of real ecosystems. Our results reveal that strong cascades occur primarily in small and weakly connected food webs, a result very much in agreement with empirical studies. The primary mechanism underlying weak or absent cascades was a strong compensatory response; in most webs predators induced large population level cascades that were masked by changes in the opposite direction by other species in the same trophic guild. Thus, the search for a general theory of trophic cascades in food webs should focus on uncovering the features of real ecosystems that promote or preclude compensation within functional guilds.

#### 1 Introduction

- <sup>2</sup> Trophic cascades occur when changes in an ecosystem's top trophic level propagate down through the
- <sup>3</sup> food web and drive changes in the biomass of primary producers (Hairston et al., 1960; Paine, 1980).
- 4 Cascades have now been documented in virtually every type of ecosystem, but neither conceptual nor
- 5 mathematical theories have been able to explain widespread variation in observed cascade strengths
- 6 (Borer et al., 2005; Shurin et al., 2010); in some ecosystems, strong cascades impact several lower trophic
- levels while in others they diminish within a single trophic level (Heath et al., 2014). Indeed, trophic
- trickles (McCann et al., 1998) weak or absent cascades in response to major changes to a food web's
- 9 top trophic level abound in nature (Brett and Goldman, 1996; Mikola and Setälä, 1998; Halaj and
- Wise, 2001). Given that human actions are disproportionately altering biomass of top predators (Estes
- et al., 2011), there is a pressing need to understand under what circumstances such changes will or won't
- cascade through complex food webs (Terborgh et al., 2010).
- Food web structure has long been predicted to regulate cascade strength (Strong, 1992; Pace et al.,

1999; Polis et al., 2000; Shurin et al., 2010) and the magnitudes of indirect effects in general (MacArthur, 1955; Yodzis, 1988). Indirect tests of this hypothesis have so far been accomplished by leveraging data on community features like functional or taxonomic diversity (Borer et al., 2005; Frank et al., 2006), in 16 hopes that these proxies for web structure could provide clues to the features of ecological networks that influence the magnitude of cascading top down effects. However results have been mixed, with studies reporting both strong (Frank et al., 2006, 2007; Baum and Worm, 2009) and weak or noisy (Borer et al., 2005; Fox, 2007) associations between diversity measures and cascade strengths. Whether data support assertions that food web structure regulates cascade strengths remains unclear, and a coherent 21 understanding of when relatively strong or weak trophic cascades occur is still lacking. One impediment to progress is that extensions of cascade theory toward species rich and topolog-23 ically complex food webs are needed to guide further empirical study. To date, cascade theory has focused largely on understanding variation in cascade strengths in model food chains (Oksanen et al., 1981; McCann et al., 1998; Heath et al., 2014; DeLong et al., 2015) and although extensions of cascade theory to alternate trophic modules exist (Bascompte et al., 2005; Fahimipour and Anderson, 2015), the mechanisms underlying variation in cascade strength in species rich and complex trophic networks remain poorly understood (Holt et al., 2010; Shurin et al., 2010). Here we use a bioenergetic food web model to explicitly study the emergence of trophic cascades in 30 species rich webs that are representative of the structure of real ecosystems following the invasion of a 31 novel top generalist predator. We demonstrate that the strongest trophic cascades occur in small and 32 weakly connected food webs — a result in agreement with some prior predictions (Pace et al., 1999; Polis et al., 2000; Fox, 2007; Shurin et al., 2010). Moreover, our results reveal that biomass compensation within producer and consumer functional guilds, whereby some species increase in biomass while others decrease proportionately, is the most common mechanism underlying weak or absent trophic cascades. Thus, the search for a general theory of trophic cascades in food webs should focus on uncovering the abiotic and biotic features of real ecosystems that promote or preclude biomass compensation and compensatory dynamics within functional guilds.

### <sup>40</sup> 2 Methods

We generated food web topologies using an ecological niche model (Williams and Martinez, 2000) and simulated the dynamics of energy flows between species using a bioenergetic model (Yodzis and Innes, 1992; Brown et al., 2004; Brose et al., 2006b; Williams et al., 2007; Williams, 2008). The niche model is discussed in detail by Williams and Martinez (2000) and was used to generate topologies for 1200 food web simulations in a factorial design: initial species richnesses of S = 10, 15, 20 and 25 were crossed with directed connectance C = 0.12, 0.16 and 0.2 as niche model parameters (4 richnesses × 3 connectances ×

100 iterations = 1200 webs total). These values of C were chosen because they encompassed a wide range
of empirically observed connectance values (Dunne et al., 2002). Webs that deviated from the precise Cvalues, contained disconnected nodes, or consisted of disconnected subgraphs were not considered.

Details of the energy flow model and parameters used are discussed by Williams et al. (2007) but
briefly, an allometrically scaled nonlinear bioenergetic model (Yodzis and Innes, 1992) was used to study
the dynamics of species biomasses and the occurrence of trophic cascades in niche model food webs when
they are subject to the invasion of a new top predator. We report results from a single ecologically
reasonable set of model parameters (see Supplementary Materials), though similar results were obtained
with other model parameterizations. Biomass dynamics were represented as

$$\frac{dB_i}{dt'} = B_i G_i(B) - \sum_{j=consumers} \frac{x_j y_{ji} B_j F_{ji}(B)}{e_{ji}}$$
(1)

$$\frac{dB_i}{dt'} = -x_i B_i + x_i B_i \sum_{j=resources} y_{ij} F_{ij}(B) - \sum_{j=consumers} \frac{x_j y_{ji} B_j F_{ji}(B)}{e_{ji}}$$
(2)

for primary producers and consumers respectively. Here  $B_i$  is the biomass of species i. All k producers were assumed to have the same body mass,  $M_k = 1$ , and time t' was scaled with producer growth rate (Williams et al., 2007). The metabolic parameter  $x_i$  is the mass specific metabolic rate of species i relative to the time scale of the system and the non-dimensional constant  $y_{ij}$  is the ingestion rate of resource i by consumer j relative to the metabolic rate of i. The efficiency  $e_{ji}$  is the fraction of the 61 biomass of resource i lost during consumption by consumer j, that is assimilated. The function  $G_i(B)$  is the normalized growth rate of primary producer population i, which follows logistic growth,  $1 - B_i/K_i$ where  $K_i$  is the carrying capacity of producer i. To control for effects of varying productivity on trophic cascade strength, we maintained constant productivity across simulations by assuming a system-wide carrying capacity K that is shared amongst i producer populations according to  $K_i = K/n_p$ , where  $n_p$ is the number of producer species in the web. The function  $F_{ii}(B)$  is the normalized multi-species functional response for consumer j and resource i, developed by Yodzis and Innes, 1992 and extended by others (Brose et al., 2006b; Williams et al., 2007; Williams, 2008). Adding consumer interference to a multispecies nonlinear functional can be represented as 71

$$F_{ji} = \frac{\omega_{ji} B_i^{1+q}}{B_0^{1+q} + d_i B_j B_0^{1+q} + \sum_k \omega_{jk} B_k^{1+q}}.$$
 (3)

Here  $d_i$  is a positive constant that sets the amount of interference in the system and the sum in the denominator is over all k resources of consumer j. The parameter  $B_0$  is the half saturation density. In order to avoid excessive extinctions or the collapse of webs following predator invasions, and permit the study of trophic cascades following major changes to web structure, we assumed that interference occurred but was weak ( $d_i = 0.5$ ) and set the shape parameter q = 0.2, which slightly relaxed consumption at

low resource biomasses — features that are both biologically realistic and likely too subtle to observe empirically (Williams, 2008). We assume passive resource switching, so  $\omega_{ij} = 1/n_{ri}$  where  $n_{ri}$  is the number of resources consumed by species i. Additional model details are discussed by Williams et al. (2007) and in Supplementary Materials. Simulations were run for 5000 model time steps at which point a top generalist predator invaded the food web. We assumed that the predator was a highly efficient generalist, with a fixed body mass 82 consistent with a large secondary consumer (see Supplementary Materials) and a scaled attack rate twice that of other species in the system. We note that the augmented predator attack rate is still within the 84 range of empirically observed values (Peters, 1983). Upon invasion, the predator had a probability of 0.5 of consuming any species in the web whose shortest path to a producer P=1; the invader can consume herbivores or omnivores that are already present in the web, but not producers or other top predators. Following the predator invasion, each system was run for a further 5000 time steps for a total 10000 time steps. Cascade strengths were measured as  $log_{10}$  response ratios  $log_{10}B_{post}/B_{pre}$ , where  $B_{post}$  and  $B_{pre}$ are aggregate producer community biomasses (summed over all  $n_p$  basal species) averaged over the final 100 time steps after and before predator invasions respectively. Likewise, consumer level effects were calculated as  $log_{10}$  response ratios of aggregate consumer biomass, where the consumer guild was defined as all species that eat producers (P = 1, where P is the shortest path length to any producer species).93 Numerical integration of ordinary differential equations was accomplished using the deSolve package in R (R Core Team, 2015). To study whether features of the initial network structure were strongly related to the response of systems to invading predators, we computed associations between the cascade strengths and a suite of 97 common network properties (Williams and Martinez, 2004; Vermaat et al., 2009) using ANOVA. The network properties we considered were species richness, connectance, characteristic path length, the fraction of species that are basal, intermediate and omnivorous, clustering coefficient, mean maximum 100 trophic similarity and Clauset-Newman-Moore modularity (Clauset et al., 2004). We note that the 101 frequentist statistical hypothesis tests employed here were not used to assess statistical significance 102 since p-values are determined by the number of simulations one chooses to run. Instead, we follow 103 the suggestion of White et al. (2014) and use the statistical model described above as a framework 104 for partitioning effect sizes and variance in these multifactorial simulations and comparing effect sizes 105 among factors. We refer to these effects below using the notation  $\beta_{variable}$  where for instance  $\beta_C$  is the 106 connectance effect, which reflects the per unit impact of scaled (Gelman, 2008) C on the strength of 107 cascades. 108 Finally, we sought to understand the mechanisms underlying weak trophic cascades, as these cascades 109 would be least likely detected in empirical studies. We operationally defined weak cascades as a less than

twofold change in aggregate producer biomass after predator invasions. One possibility is that weak

cascades are caused by diffuse predator effects (sensu Yodzis, 2000), whereby predator consumption is spread over multiple resources leading to overall weak biomass responses at the population scales. In this scenario, species in each lower trophic level change only slightly in the same direction, and strong community level biomass responses fail to emerge. Alternatively, weak cascades could occur even in the presence of major changes to population biomasses if changes in strongly depressed species are offset by compensatory changes in the opposite direction by other species (i.e., biomass compensation; Gonzalez and Loreau, 2009) in the producer or consumer guilds. To quantitatively assess these possibilities, we present a measure  $\mu$  that quantifies the degree of biomass compensation among populations i in a trophic guild as

$$\mu = 1 - \frac{\left|\sum_{i \in s} B_{i,post} - B_{i,pre}\right|}{\sum_{i \in s} \left|B_{i,post} - B_{i,pre}\right|} \tag{4}$$

where the sum is over all s species in a trophic guild (e.g., producers). This metric  $\mu$  varies from 0 to 1, with 0 indicating that all species within a guild changed in the same direction (the biomass of all populations increased or decreased) and 1 indicating perfect biomass compensation. If weak trophic cascades are typically accompanied by small  $\mu$  values, then we conclude that weak cascades usually occur because top down effects are too diffuse to effect strong changes in aggregate producer biomass. Conversely, if weak cascades are typically accompanied by large  $\mu$ , then we conclude that compensatory changes in the opposite direction by species in the same guild lead to a small net changes in aggregate biomass. Herein, we refer to compensation in the producer and consumer guilds as  $\mu_R$  and  $\mu_N$ .

#### 129 3 Results

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Producers changed by a factor of 1.7 on average across all simulations, and twofold changes in producer 131 biomass occurred in only 31% of webs. Predator facilitation of producers was strongest in small and 132 weakly connected webs (Fig. 2;  $\beta_S = -0.111$ ,  $\beta_C = -0.012$ ). Cascade strengths were also associated 133 with other topological properties commonly used to describe web structure (Williams and Martinez, 2004; Vermaat et al., 2009). The strongest associations were observed between producer log response ratios and S, the fraction of basal species, the fraction of intermediate species and mean maximum 136 trophic similarity (Table 1). 137 The magnitudes of consumer log response ratios were more strongly correlated with most food web 138 properties (Table 1), suggesting that the sensitivity of a guild's log response ratio to initial network 139 conditions may depend on trophic position; topology appears to exhibit relatively strong associations with 140 changes in consumer level biomass following novel predator invasions compared to lower trophic levels. 141 Depression of consumer biomass by invading predators was strongest in small and weakly connected 142 networks (Fig. 2;  $\beta_S = 0.741$ ,  $\beta_C = 0.156$ ) with fewer basal species and less modular, more clustered

Predator invasions had moderate effects on aggregate producer biomass in most food webs (Fig. 1).

network configurations (Table 1).

Producer compensation  $\mu_R$  was negatively correlated with cascade strengths across all simulations 145 (Fig. 3a; Pearson's r = -0.34), suggesting that biomass compensation among producers commonly masked cascades at the community scale (e.g., compare Figs. 3b & 3c). This result is recapitulated by 147 the high frequency of simulations characterized by stronger trophic cascades and almost no producer compensation (Fig. 3a, dark shaded region). Indeed, of the webs that exhibited weak producer cascades 149 (i.e., aggregate producer biomass increased by less than a factor of 2), 90% contained at least one 150 producer population that more than doubled despite the absence of a strong community level cascade. 151 Taken together this suggests that weak cascades were in large part caused by producer compensation, 152 leading to a small net changes in aggregate biomass. 153

Compensation in the consumer guild increased strongly with S and C (Fig. 4), explaining the shift in consumer effect size distributions toward zero visible in Figs. 1e-h and Fig. 2. This suggests that two separate compensation mechanisms could explain weak cascades in webs. The first occurred primarily in smaller webs, when strong depression of consumers was transmitted to producer populations but failed to manifest at the guild scale because changes in some populations were offset by others in the opposite direction (i.e., producer compensation). The second occurred primarily in larger webs (Fig. 4), when top-down predator effects were immediately diminished in the consumer trophic guild due to consumer compensation. The strongest cascades occurred when the degrees of both producer and consumer compensation were low, which was most likely in small, weakly connected webs.

#### <sup>163</sup> 4 Discussion

Our modeling study found that strong trophic cascades at the scale of the producer community are more likely to occur in smaller, less connected ecological communities, a result that is in agreement with some 165 previous interpretations of indirect effects and trophic cascades (MacArthur, 1955; Pace et al., 1999; 166 Frank et al., 2006; Shurin et al., 2010). In most webs (90% of all simulations), at least one producer 167 species doubled or more in biomass, yet strong community scale cascades occurred in only thirty percent 168 of simulations. Strong population level cascades were often offset by an opposite biomass change in 169 other species so that the overall producer community biomass wasn't strongly affected. Thus, restricting 170 attention to trophic cascades as measured by changes in the overall biomass of producer species makes it 171 much less likely that the effects of an invading species will be detected. Strong top-down effects still occur in large and complex ecological networks, but observing them requires finer-grained observations than simply measuring total plant biomass (Polis et al., 2000). In almost all communities, the introduced top 174 species had a strong effect on both the relative biomass of species and the dynamics of the community. Shifts in relative species composition due to compensation within a community are more common than 176

changes in the overall community biomass, and may be a potentially useful indicator for species invasions (Schmitz, 2006).

Weaker cascades in large highly connected webs have been attributed to weaker and more diffuse 179 interactions among trophic levels in these systems (Leibold et al., 1997; Pace et al., 1999; Shurin et al., 180 2010). However, the observation that compensation frequently operated in multiple trophic guilds suggests a new hypothesis for the emergence of trophic cascades in complex food webs. Namely, changes at 182 the top of webs have some chance of diminishing due to compensation within each trophic guild, as they 183 cascade down to producers. If the trophic network is structured in a way that precludes compensation 184 from occurring in any of these guilds, then a strong cascade will emerge. Alternatively, top-down regula-185 tion has the capacity to diminish within a single trophic level if the propensity for compensation is high 186 in that particular system, which can result from particular network configurations or exogenous abiotic 187 forcing in real ecosystems (Gonzalez and Loreau, 2009). Experimental tests of this hypothesis could be 188 accomplished by adding conspecific generalist predators to replicate food webs with known topologies (e.g., experimentally assembled micro- or mesocosms) and measuring them repeatedly through time. However, replicated food web experiments with repeated measures are scant (Fahimipour and Hein, 191 2014) and to our knowledge no such data exist to test the results presented here. 192

The present study looks at the role of increasing web size and structural complexity on trophic 193 cascades and the detection of the effects of species introductions. The model used, while more complex 194 than those typically used in trophic cascade studies, is still highly idealized. The dynamics of real 195 ecosystems often include many other non-trophic processes (Kéfi et al., 2015) which might dampen (or 196 magnify) the cascading influence of top predators (Polis and Strong, 1996). One such example is that 197 our study was restricted to models of closed systems. Evidence of cross-ecosystem cascades (Knight 198 et al., 2005) and the influence of resource colonization rates on cascades (Fahimipour and Anderson, 199 2015) suggest that extensions of our model to open systems will be a promising enterprise for further theoretical study. 201

Identifying the abiotic and biotic features of ecosystems that regulate trophic cascades is a fundamental issue in ecology (Polis et al., 2000; Terborgh et al., 2010) and a practical problem for the management
of invasive species, agricultural pests and zoonotic disease (Estes et al., 2011). While the present study
identifies features of model food web architecture that influence cascades, the potential for compensation (Gonzalez and Loreau, 2009), complex indirect interactions and feedbacks (Yodzis, 2000) in real
world networks together with insufficient data (Shurin et al., 2010) and issues of scale (Polis et al., 2000)
combine to make the development of a predictive cascade theory of food webs a difficult problem.

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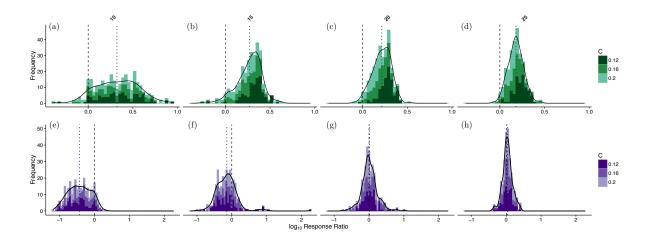
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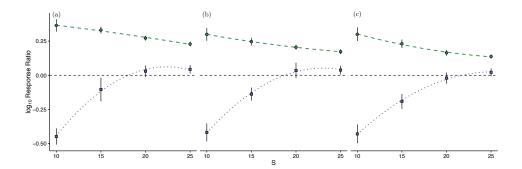
### Figure Captions

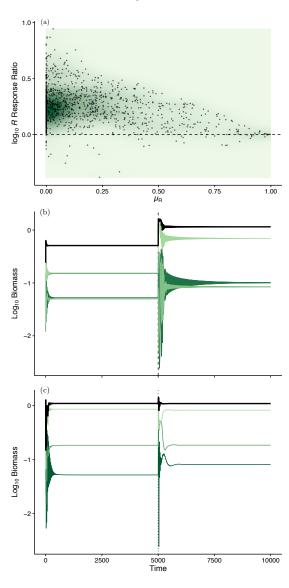
- Fig. 1. (a—d) Stacked histograms of producer cascade strength frequency distributions for webs of different richness (panel columns) and connectance (green shading) values. The green dotted lines mark mean cascade strengths for reference. Smoothing was accomplished using a Gaussian kernel. (e—h) Stacked histograms of consumer cascade strength frequency distributions for webs of different richness (panel columns) and connectance (purple shading) values. The purple dotted lines mark mean consumer cascade strengths for reference. Smoothing was accomplished using a Gaussian kernel.
- Fig. 2. Relationships between S, C and cascade strengths in the producer (green circles) and consumer (purple squares) guilds. Points and error bars represent mean cascade strength  $\pm 2$  SEM and lines show results of *loess* regression to raw simulated data. Panels (a), (b) and (c) correspond to C values of 0.12, 0.16 and 0.2 respectively.
- Fig. 3. (a) Level plot showing the negative relationship between the producer cascade strengths and
  the degree of producer compensation,  $\mu_R$ . Points represent individual simulations. The background
  is shaded according to a Gaussian kernel used for density estimation, where darker shades of green
  represent denser regions. A high density of stronger cascades with near-zero producer compensation is
  visible. (b) Example of a relatively strong cascade where compensation is weak. Colored green lines
  represent individual producer populations and the thick black line is the aggregate producer biomass.
  A dotted line marks the predator invasion. (c) Example of a weak cascade due to strong producer
  compensation.
- Fig. 4. Relationships between S, C and compensation in the producer (green circles) and consumer (purple squares) guilds. Points and error bars represent mean compensation values  $\pm 2$  SEM and lines show results of *loess* regression to raw simulated data. Panels (a), (b) and (c) correspond to C values of 0.12, 0.16 and 0.2 respectively.

### Table Captions

Table 1. Results of ANOVA tests. The Variable column indicates the dependent variable to which statistics refer. The food web properties were species richness (S), directed connectance (C), characteristic path length (CPL), the fraction of species that are basal  $(Frac.\ B)$ , intermediate  $(Frac.\ I)$  and omnivorous  $(Frac.\ Om)$ , Clauset-Newman-Moore modularity, clustering coefficient and mean maximum trophic similarity. The  $\beta$  and sums-of-squares columns indicate the regression coefficients and model sums of squares respectively.







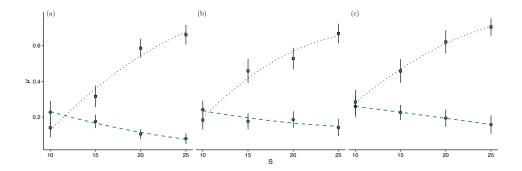


Table 1: Results of ANOVA tests

Variable	Food Web Property	β	Sum-of-squares
Producer Response Ratio			
	S	-0.111	31.87
	С	-0.012	15.33
	CPL	0.08	0.53
	Frac. B	0.21	1.86
	Frac. I	-0.116	4.83
	Frac. Om	0.001	0.06
	Modularity	0.014	0.01
	Clustering Coefficient	0.009	0.19
	Mean Maximum Similarity	-0.095	1.48
Consumer Response Ratio			
Contemner Response Russie	S	0.741	84.46
	C	0.156	0.58
	CPL	0.002	0.11
	Frac. B	0.218	4.24
	Frac. I	-0.084	6.95
	Frac. Om	0.014	0.03
	Modularity	0.077	0.55
	Clustering Coefficient	-0.084	0.93
	Mean Max Similarity	0.038	0.24

### 349 Supplementary Methods

352

Metabolic parameters in the bioenergetic model (Yodzis and Innes, 1992; Brose et al., 2006b) are given
by

$$x_i = \frac{a_{Ti}}{a_{rk}} \frac{M_k}{M_i}^{0.25} \tag{5}$$

$$y_{ij} = \frac{a_{ji}}{a_{Ti}}. (6)$$

Here,  $M_i$  is the mass of an individual of species i and  $M_k$  is the mass of primary producers used for 353 normalizing the time scale. The constants  $a_T$ ,  $a_r$  and  $a_j$   $(mass^{0.25} \times time^{-1})$  were previously determined from empirical data on the allometry of metabolism, production, and maximum consumption respectively. 355 We assumed that all species were invertebrates, and so  $a_r = 1$ ,  $a_T = 0.314$  and  $y_{ij} = 8$  (see Brose et al. 356 (2006b) for the derivation of these values). The assimilation efficiency  $e_{ij} = 0.45$  for consumption of 357 producers and  $e_{ij} = 0.85$  for consumption of consumers. In order to reduce the size of the parameter 358 space being explored, all species in a web were assumed to have a constant consumer-resource body 359 size ratio Z so that the mass of species i was  $M_i = M_k Z^P$  where P is shortest path length between 360 species i and any producer. We report simulations in which Z=42. This value represents the mean 361 predator-prey body mass ratio reported by Brose et al., 2006a, although the results presented herein 362 were not sensitive to the choice of Z across its biologically relevant range. We assumed that the predator 363 had a fixed body mass consistent with a large secondary consumer  $M_{pred} = Z^{2.5}$ . To ensure predators were not entering webs in which many species had gone extinct prior to their arrival, we set a limit on the maximum allowable number of extinctions prior to invasions at two, using  $B_i < 1 \times 10^{-15}$  as the extinction threshold. In the event of extinctions before predator arrival, we allowed the extinct taxa to 367 reinvade the system at an initial biomass equal to the extinction threshold. We report results for systems 368 in which  $B_0 = 0.25$  and the system-wide carrying capacity K = 5. The initial biomass of each species 369 was uniformly drawn from [0.01, 0.1] for all simulations. 370