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### Authors

Eddy, Tyler D  
Bernhardt, Joey R  
Blanchard, Julia L  
[et al.](#)

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# 1 Energy flow through marine ecosystems: confronting transfer 2 efficiency

3

4 Tyler D. Eddy<sup>1,2</sup>, Joey R. Bernhardt<sup>3</sup>, Julia L. Blanchard<sup>4,5</sup>, William W.L. Cheung<sup>3</sup>, Mathieu Colléter<sup>6</sup>,  
5 Hubert Du Pontavice<sup>3,7</sup>, Elizabeth A. Fulton<sup>4,8</sup>, Didier Gascuel<sup>7</sup>, Kelly A. Kearney<sup>9</sup>, Colleen M. Petrik<sup>10</sup>,  
6 Tilla Roy<sup>11,12</sup>, Ryan R. Rykaczewski<sup>1,13</sup>, Rebecca Selden<sup>14</sup>, Charles A. Stock<sup>15</sup>, Colette C.C. Wabnitz<sup>3,16</sup>,  
7 Reg A. Watson<sup>4,5</sup>

8

9 <sup>1</sup>Nippon Foundation Nereus Program, Baruch Institute for Marine & Coastal Sciences, University of  
10 South Carolina, SC, US

11 <sup>2</sup>Centre for Fisheries Ecosystems Research, Fisheries & Marine Institute, Memorial University of  
12 Newfoundland, St. John's, NL, Canada

13 Corresponding author: tyler.eddy@mi.mun.ca; @tyzissou

14 <sup>3</sup>Nippon Foundation Nereus Program and Changing Ocean Research Unit, Institute for the Oceans and  
15 Fisheries, University of British Columbia, Vancouver, BC, Canada

16 <sup>4</sup>Centre for Marine Socioecology, University of Tasmania, Hobart, Tasmania, Australia

17 <sup>5</sup>Institute for Marine and Antarctic Studies, University of Tasmania, Australia

18 <sup>6</sup>BLOOM Association, Paris, France

19 <sup>7</sup>ESE, Ecology and Ecosystem Health, Agrocampus Ouest, Rennes, France

20 <sup>8</sup>CSIRO Oceans and Atmosphere, Hobart, Tasmania, Australia

21 <sup>9</sup>Joint Institute for the Study of the Atmosphere and Oceans (JISAO), University of Washington, WA, US

22 <sup>10</sup>Department of Oceanography, Texas A&M University, College Station, TX, US

23 <sup>11</sup>Ecoceana, Ecosystem, Climate, and Ocean Analysis, Paris, France

24 <sup>12</sup>Department of Geosciences, L'École Normale Supérieure, Paris, France

25 <sup>13</sup>Pacific Islands Fisheries Science Center, NOAA National Marine Fisheries Service, Honolulu, HI, US

26 <sup>14</sup>Department of Biological Sciences, Wellesley College, Wellesley, MA, USA

27 <sup>15</sup>Stockholm Resilience Centre, Stockholm University, Stockholm, Sweden

28 <sup>15</sup>Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration,

29 Princeton, NJ, US

30

31 Keywords (2-6): trophic ecology; food web; trophic efficiency; energy transfer; climate change; fishing

32 impacts

33

34

35 Highlights

36 • Transfer efficiency is a key parameter describing ecosystem structure and function and is used  
37 to estimate fisheries production, however, it is also one of the most uncertain parameters.

38 • Questions remain about how habitats, food resources, fishing pressure, spatiotemporal scales,  
39 temperature, primary production, and other climate drivers impact transfer efficiency.

- 40 • Direct measurements of transfer efficiency are difficult, but observations of marine population  
41 abundances, diets, productivity, stable isotope analysis, and models integrating these  
42 constraints can provide transfer efficiency estimates.
- 43 • Recent estimates suggest that transfer efficiency is more variable than previously thought,  
44 compounding uncertainties in marine ecosystem predictions and projections.
- 45 • Increased understanding of factors contributing to variation in transfer efficiency will improve  
46 projections of fishing and climate change impacts on marine ecosystems.

47

## 48 Glossary

- 49 - Assimilation efficiency: proportion of ingested material that is broken down by digestive  
50 enzymes to fuel the organism's metabolic processes. Unassimilated material is egested.
- 51 - Energy flux model: a model that quantifies relationships between biodiversity and the flow of  
52 energy through ecosystems
- 53 - Food web: a system of interconnected feeding relationships or food chains. Illustrations depict  
54 resources and consumers with nodes linked by lines that symbolize a feeding relationship (e.g.  
55 Figure 1D). Nodes can represent predator and prey, species, trophic levels, functional groups or  
56 size classes.
- 57 - Food web model or ecosystem model: a mathematical representation of how energy or  
58 biomass flows from primary producers to primary consumers and then to secondary consumers  
59 and higher predators.
- 60 - Predator-prey mass ratio: the ratio of the average mass of an individual predator to that of its  
61 prey.

- 62 - Production: the generation of biomass or energy. Primary production refers to the synthesis of  
63 organic compounds from carbon dioxide most often via photosynthesis. Secondary production  
64 involves the generation of biomass through consumption of another organism.
- 65 - Productivity: the rate of production.
- 66 - Resilience: ability of a population or ecosystem to recover to its original state following a  
67 disturbance.
- 68 - Size spectrum model: a mathematical representation of a food web that groups individuals by  
69 their sizes.
- 70 - Trophic level model: a mathematical representation of a food web that groups individuals by  
71 their position in a food chain.
- 72 - Stable isotopes: naturally occurring, non-radioactive atoms of the same element that have  
73 different numbers of neutrons. The isotope with fewer neutrons is lighter in mass, which results  
74 in faster chemical reaction rates and may lead to a preference for its uptake by organisms.  
75 Comparing ratios of carbon and nitrogen stable isotopes in organismal tissues to ratios in their  
76 prey can elucidate the processes that formed these tissues and estimate the organism's trophic  
77 level.
- 78 - Transfer efficiency: the proportion of resource production converted into consumer production.  
79 Transfer efficiency is often calculated as the proportion of production passed from one node to  
80 another in a food web.
- 81 - Trophic level: the position of an individual within a food web based on the number of feeding  
82 links between it and the primary producer. Primary producers such as phytoplankton and  
83 plants have a trophic level of 1, herbivores have a trophic level of 2, carnivores have a trophic  
84 level of at least 3. Non-integer trophic levels result from mixed diets. Detritus is often also  
85 assigned a trophic level of 1.

86

87 Abstract

88 Transfer efficiency is the proportion of energy passed between nodes in food webs. It is an emergent,  
89 unitless property that is difficult to measure and responds dynamically to environmental and ecosystem  
90 changes. Because the consequences of changes in transfer efficiency compound through ecosystems,  
91 slight variations can have large effects on food availability for top predators. We review processes  
92 controlling transfer efficiency, approaches to estimate it, and known variations across ocean biomes.  
93 Both process-level analysis and observed macroscale variations suggest that ecosystem-scale transfer  
94 efficiency is highly variable, impacted by fishing, and will decline with climate change. It is important  
95 that we more fully resolve the processes controlling transfer efficiency in models to effectively  
96 anticipate changes in marine ecosystems and fisheries resources.

97

## 98 **Efficiency of energy transfer through food webs**

99 **Transfer efficiency** (see Glossary) is an emergent, unitless property that quantifies the fraction  
100 of energy passed from one node to another in a **food web**. It is often estimated as the ratio of  
101 **production** at a **trophic level** relative to one trophic level below (Figure 1; [1-5]). A high transfer  
102 efficiency means that a greater proportion of production at lower trophic levels is converted to  
103 production at the upper trophic levels. Transfer efficiency is a critical factor shaping marine  
104 ecosystems, as even subtle shifts in transfer efficiency can compound across trophic levels and lead to  
105 profound differences in abundances of top predators (Boxes 1, 2; [2,6-10]) and sustainable fishing rates  
106 [4,5,11]. Fisheries catches, for example, vary by more than two orders of magnitude across heavily  
107 fished systems despite variations in primary production within a factor of four [8]. Cross-biome

108 gradients in transfer efficiencies underlie these differences, with high transfer efficiencies accentuating  
109 fish biomass peaks in high primary production areas and low efficiencies deepening lows in oligotrophic  
110 (low primary production) systems [2,8]. As climate change affects ocean temperature and primary  
111 production [12], increased transfer efficiencies could compensate for changes in primary production.  
112 Alternatively, decreased transfer efficiencies could exacerbate declines in primary production, reducing  
113 potential fisheries harvest from the oceans [13,14].

114         Transfer efficiency is often illustrated using a trophic pyramid (Figure 1A). The trophic pyramid  
115 presents a useful and conceptually simple depiction of trophodynamics – the thinning of the trophic  
116 pyramid at higher trophic levels is indicative of energy not transferred, resulting in decreasing  
117 production. Generally, a transfer efficiency of ~10%, based on early model estimates [4], is used as a  
118 characteristic value for marine ecosystems (Figure 1A).

119         Despite its recognized importance, transfer efficiency persists as a dominant source of  
120 uncertainty in our understanding of current marine ecosystems and projected changes. This reflects  
121 three challenges: 1) transfer efficiency is determined by diverse processes at multiple scales with  
122 potentially complex dependencies on environmental and ecosystem properties, 2) it is difficult to  
123 measure and estimate, and 3) current models used to predict marine resource trajectories generally  
124 have highly simplified representations of it. This contribution provides a synthesis of these challenges,  
125 our present understanding of transfer efficiency, and a summary of estimates of its value.

126

## 127 **Processes controlling transfer efficiency**

128         A complex set of processes control the distribution of production among trophic levels (Figure  
129 1). We group this diversity of processes into three categories operating at different scales: metabolism  
130 at the individual organism scale (Figure 1B), life cycle at the species population scale (Figure 1C), and  
131 food webs at the ecosystem scale (Figure 1D). The integration of all these processes and scales

132 ultimately determines the trophic organization of an ecosystem, the production of each level within it,  
133 and the efficiency of energy transfer through it.

134

### 135 *Metabolism*

136 At the individual level, numerous metabolic processes modulate the translation of ingested  
137 material to the production of new organic matter (Fig. 1B). Once material is ingested, a fraction of it is  
138 broken down by digestive enzymes to fuel the organism's metabolic processes. This fraction is referred  
139 to as the **assimilation efficiency**, with unassimilated material lost to egestion of dissolved and  
140 particulate organic material. Assimilated material is then partitioned between catabolic (energy  
141 producing) and anabolic (tissue building) processes, with anabolic processes only possible once  
142 catabolic needs are met. Catabolic metabolism is often further divided into basal (or maintenance) and  
143 active respiration, with the former costs incurred regardless of the organism's activity, and the latter  
144 increasing with movement and feeding levels. Only the anabolic investment is reflected in transfer  
145 efficiency, and each of the processes toward this final investment have complex environmental  
146 dependencies [15].

147 The metabolic theory of ecology [16] predicts that increasing temperature increases the rates  
148 of most biological processes to a point, including the rates at which organisms respire, [16-17], grow,  
149 and reproduce [18,19,22]. Metabolic and growth rates of primary producers are generally less  
150 temperature-sensitive than those of consumers [17] and can have different temperature dependencies  
151 [20]. This can lead to differential rates of consumer production relative to primary production as  
152 temperature changes [21], thus affecting transfer efficiency. In many cases, increasing ocean  
153 temperatures are associated with increasing stratification, decreased resource availability [19] or  
154 reduced food quality [22], complicating detection of direct temperature effects. Ecological  
155 stoichiometry has demonstrated theoretically and empirically that nutrition of prey relative to predator



156 demands determines transfer efficiency [23]. Consumers feeding on high quality prey (i.e., rich in  
157 macronutrients and essential fatty acids) have higher growth rates [24] resulting in greater transfer  
158 efficiencies [25-28].

159

### 160 *Life cycle*

161 Life cycles (Fig. 1C) shape the translation of anabolic reproductive investments into production  
162 observed at each trophic level. The most volatile life cycle element for an individual species is survival  
163 through early life stages (i.e., recruitment in the fisheries context [29]). Subtle changes in food  
164 resources and metabolism have been implicated in large changes in early stage growth and survival at  
165 the species level [30-32]. Changes in timing of food availability due to climate change can have strong  
166 impacts on the reproductive success of a species [33]. Since volatility in survival is species-specific, food  
167 web structure can be maintained by having one species in a similar trophic position compensate for  
168 another, resulting in **resilience** in trophic structure and transfer efficiency at the ecosystem level.  
169 However, fluctuations in species abundances can control energy pathways through food webs, and  
170 systems dominated by a small number of species may have limited resilience, [34-35]. For example, a  
171 food web with multiple forage fish species will be more resilient to changes in abundance of a specific  
172 forage fish species due to reduced reproduction, as the other species can play the same trophic role and  
173 provide alternative energy pathways to higher trophic levels (Figure 1D). Furthermore, climate change  
174 is projected to affect the timing of consumer life cycles and critical resources, increasing the probability  
175 of extreme mismatches affecting species reproduction and growth, capable of restructuring food webs  
176 and reducing ecosystem level transfer efficiencies [36-40].

177

### 178 *Food web structure*

179           Transfer efficiency is further shaped at the ecosystem scale by a diversity of food web  
180 interconnections and non-predatory fluxes of organic material. Alternative pathways for primary  
181 production through food webs have different efficiencies and the emergent transfer efficiency  
182 integrates across these pathways. Prominent examples from the plankton food web are small  
183 phytoplankton dominated oligotrophic systems where multiple zooplankton consumer links are  
184 required to reach forage fish [2,41]. These systems are contrasted by productive coastal areas  
185 dominated by large phytoplankton, where forage fish are often only one trophic level removed from  
186 phytoplankton [2,41]. The partitioning between these pathways can be controlled by passing eddies  
187 and fronts leading to a time-varying trophic organization that does not always reflect the average state  
188 [42]. The spatial distribution or patchiness of prey can also influence transfer efficiency. Variation in  
189 phytoplankton abundances at the micro- to meso-scales has been suggested to enhance production,  
190 which is especially important for explaining high transfer efficiencies in oligotrophic regions [43].

191           Non-predatory loss mechanisms include any food web processes that prevent energy from  
192 reaching higher trophic (e.g., burial of organic matter that has sunk to the sea floor – Figure 1D). Viral  
193 lysis, for example, cycles bacterial and phytoplankton biomass back to dissolved organic material where  
194 detritivores such as bacteria are the consumers [44]. Exudation (leakage) of fixed organic carbon by  
195 phytoplankton [45] has similar trophic consequences. If viewed as external to the natural ecosystem,  
196 fishing also results in a removal of energy that reduces ecosystem-scale transfer efficiency between  
197 subsequent trophic levels. For pelagic ecosystems, the sinking of organic material as phytoplankton  
198 aggregates, fecal pellets, jelly falls or seasonal/diel migrations also present losses of energy losses that  
199 are ultimately reflected in transfer efficiency (Figure 1D); [2,41,46-48]. The environmental,  
200 physiological, and ecological dynamics governing each of these processes are as complex as those  
201 governing trophic linkages, and alternative assumptions about the form of these losses can have  
202 significant effects on emergent transfer efficiency [49].

203 Benthic and pelagic systems often have different energy pathways, which can lead to  
204 differential transfer efficiencies. In benthic ecosystems, the flux of detritus from surface waters and  
205 vertically migrating organisms provide the primary energy inputs [50-51]. Analysis of global marine  
206 catch data has provided modest evidence for higher transfer efficiencies associated with benthic food  
207 webs [8], where food resources are concentrated in a two-dimensional space requiring less foraging  
208 [52]. However, in lake ecosystems, there is no clear agreement whether benthic or pelagic food webs  
209 exhibit higher transfer efficiency [53-55]. In near-shore coastal ecosystems, benthic and pelagic  
210 ecosystems are frequently coupled, and dynamic linkages in energy transfer are a key component of  
211 how they function [50]. For example, in coral reef ecosystems – known to be nutrient limited yet  
212 paradoxically highly productive and biodiverse – sponges consume dissolved organic material and  
213 excrete their cells as detritus, providing a critical energy pathway to higher trophic levels that increases  
214 transfer efficiency [51]. Additionally, cryptobenthic fishes on coral reefs have been found to provide  
215 larvae in the near-reef pelagic zone accounting for almost 60% of consumed reef fish biomass,  
216 providing a key energy pathway to higher trophic levels, producing greater ecosystem-scale transfer  
217 efficiency [56].

218 Other food web factors impacting transfer efficiency include mixotrophs (capable of being  
219 producers and consumers) in planktonic food webs due to their ability to photosynthesize to  
220 compensate for respiratory losses or to reduce energy consumption by catabolic respiration [57].  
221 Predator and prey size diversity have also been found to affect transfer efficiencies in planktonic  
222 communities, with transfer efficiency decreasing with increasing prey size diversity and conversely  
223 increasing with greater predator size diversity [42]. Additionally, growth in individual prey size drives  
224 declines in transfer efficiency [15]. The wide range of processes and scales that influence transfer  
225 efficiency result in challenges in its estimation.

226

## 227 Estimating transfer efficiency

228 While transfer efficiencies emerge from diverse metabolic, life cycle, and food web processes,  
229 estimating transfer efficiency requires knowledge of just two fundamental properties: the trophic level  
230 of organisms within an ecosystem determined by their diets, and the production at each trophic level.  
231 Neither of these, however, is easy to measure. Indirect transfer efficiency estimates thus rely on  
232 combining limited direct measurements, theory, and models. Although challenges exist to estimate  
233 transfer efficiency in aquatic ecosystems, there are several approaches that can be used, summarized  
234 below.

235

### 236 *Diet estimates*

237 Accurate accounting of trophic level is challenging. Trophic level quantifies the number of  
238 feeding links between an organism and primary producers (Figure 1), and is a function of an organism's  
239 diet, and the diet of their prey, etc. Trophic level can be estimated from diets through direct  
240 observation of feeding behaviour and stomach content analysis. Alternatively, **stable isotope** ratios  
241 can reveal trophic level due to fractionation that occurs during assimilation of prey. However,  
242 estimating trophic level is highly dependent on how one chooses to resolve the relevant food web  
243 nodes (individuals, populations, species, functional groups, size classes). It is further complicated by  
244 temporal variation in the diet of individuals depending on the species, food availability, and life stages  
245 present at any given time (e.g. juveniles and adults of the same species often eat different prey). As the  
246 trophic level of each relevant food web unit is required to calculate transfer efficiency from one level to  
247 the next, any uncertainty in assigning trophic level to a single group will be propagated to calculations  
248 of transfer efficiency for the ecosystem.

249 Stable isotopes of nitrogen and carbon used jointly with biomass spectra can elucidate feeding  
250 relationships in food webs [58-60]. Due to differences in fractionation, the tissues of predators  
251 preferentially incorporate heavier nitrogen isotopes from their diet, resulting in a systematic  
252 enrichment in nitrogen-isotope ratio ( $\delta^{15}\text{N} = ^{15}\text{N}/^{14}\text{N}$ ) with increasing trophic level [61,62]. Size-  
253 fractionated stable isotope analysis is commonly used to quantify the flow of energy in **size spectrum**  
254 **models** and to inform **predator-prey mass ratios** (PPMR [58,63-64]). The slope ( $b$ ) of  $\delta^{15}\text{N}$ , an indicator  
255 of trophic level, as a function of logarithmic body size class is first used to estimate PPMR:  $PPMR = n^{(\Delta/b)}$ ,  
256 where  $\Delta$  is the fractionation of  $\delta^{15}\text{N}$  and  $n$  is the logarithmic base of the size classes [65]. Size spectra  
257 are often used in aquatic ecosystems to illustrate the relationship between abundance and/or biomass  
258 with size, again grouped in logarithmic classes. Biomass size spectra provide information about the  
259 amount of production in each size class, under the metabolic theory assumption that individual  
260 biomass production is a function of body size [66-67]. Combining the production per size class from the  
261 slope of biomass size spectra data ( $\beta$ ), and the change in trophic level with size from PPMR, allows the  
262 estimation of transfer efficiency (TE):  $TE = PPMR^{\beta+0.75}$  [17,59,68]. One caution, however, is that stable  
263 isotope estimates of PPMR have been shown to be particularly sensitive to the trophic enrichment  
264 factors used in analyses [62,69-71]. For example, using a trophic enrichment factor of 2 instead of 3.4  
265 can yield PPMR estimates that are 1-3 orders of magnitude lower, and transfer efficiency estimates that  
266 are 2-4 times higher [69].

267

#### 268 *Production estimates*

269 **Productivity** – the rate at which energy or biomass is generated – can be estimated by tracking  
270 population development through time by assessing mass-specific growth and mortality rates using size  
271 or age-structured observations [72]. Quantification of primary production in the oceans relies on  $^{14}\text{C}$

272 measurements [73] and can be estimated by satellite – albeit with some uncertainty in deeper waters  
273 [74] – by leveraging diverse algorithms (e.g., [75]). Empirical production to biomass ratios from  
274 metabolic theory can be applied to abundance data to estimate productivity where it is not possible to  
275 make such observations of primary production or to estimate production of higher trophic levels [72].  
276 These ratios are generally combined with other variables (e.g., biomass) to form an integrated picture  
277 of an ecosystem from which transfer efficiencies can be derived [48,76] .

278           Production-based transfer efficiency estimates for temperate Northern hemisphere marine  
279 ecosystems yielded an average transfer efficiency of 13% (ranging from 11-17%) for trophic levels 1-2  
280 (phytoplankton to herbivorous mesozooplankton and benthic organisms) and an average transfer  
281 efficiency of 10% (ranging from 7-12%) for trophic levels 2-3 (zooplankton and benthic organisms to  
282 fish) [76]. Laboratory plankton feeding experiments have yielded higher transfer efficiencies than wild  
283 populations because wild populations often feed at suboptimal prey concentrations (which can be  
284 controlled in the lab) and lab conditions can prevent loss of production to the microbial loop that is not  
285 consumed in wild populations (Figure 1D; [76]). The impacts of energy fluxes through these different  
286 food web pathways highlight the importance of integrating processes at the ecosystem scale.

287

#### 288 *Model based estimates*

289           Given the wide range of processes controlling, and factors affecting transfer efficiency at  
290 multiple scales, models can be used as an integration tool, to test hypotheses, and to make predictions.  
291 **Food web models** provide a means of integrating all available diet and production data. Transfer  
292 efficiency values can be estimated from food web models by calculating how much energy or biomass  
293 production is transferred between species, functional groups, size classes or trophic levels (e.g. [77-79]).  
294 However, *a priori* estimates of transfer efficiency have often directly or indirectly influenced the choice

295 of model parameters and processes that modellers consider to describe energy flows. For example, the  
296 10% transfer efficiency estimated by Pauly and Christensen [4] and the 5%, 10%, and 15% efficiencies  
297 for upwelling, temperate, and tropical ecosystems respectively, estimated by Coll et al. [80] and  
298 Libralato et al. [5] often guide the choice of parameters in the well-established and commonly-used  
299 food web and fisheries modelling framework, Ecopath with Ecosim [77]. However, if all other model  
300 parameters are fixed, the mass-balancing of Ecopath with Ecosim models can be used to estimate  
301 transfer efficiencies within food webs.

302         The emergence of regularities in observation-based estimates provides a foothold for  
303 modellers simulating the flow of energy through marine ecosystems using theoretical approaches.  
304 Early models of biomass spectra lack mechanistic details, but can resolve patterns emerging from  
305 transfer efficiency estimates [67,81,82]. **Energy flux models** aim to find relationships between  
306 biodiversity and the flow of energy through ecosystems and include efficiency terms, however have not  
307 yet been applied to estimate transfer efficiency [83-84]. **Size spectrum models** are based on  
308 allometric principles that predators tend to be bigger than their prey, so that species can be ignored,  
309 and size classes of organisms can be used to track energy flow instead. Size spectrum models have  
310 been used to derive transfer efficiency by scaling up from individual level principles of how  
311 consumption, search rate, prey choice, and assimilation efficiency vary with body size [15,48,85]. As  
312 the number of observational studies reporting these properties grows, it is becoming possible to  
313 examine how transfer efficiency differs with both size and functional group – e.g. small versus large  
314 zooplankton, filter feeders versus mobile predatory benthic invertebrates, fishes of different sizes and  
315 feeding modes, ectotherms versus endotherms – and to add these trait-specific properties to models  
316 [52,86].

317         Process-based plankton food web models from global Earth system models produce primary  
318 and secondary production estimates that can be used to calculate transfer efficiency and global

319 fisheries catches at the large marine ecosystem (LME) scale [8]. Using this approach, empirical model  
320 predictions best matched observed catches when the microbial loop and benthic and pelagic  
321 compartments were included in the formulation [8]. The ecosystem transfer efficiencies needed to  
322 reconcile simulated primary production with observed fish catches were 14% on average, with tropical  
323 and subtropical systems reduced at 74% of temperate values, and benthic transfer efficiencies greater  
324 than pelagic values [8].

325 FEISTY is a spatially explicit, mechanistic model of three fish functional types based on  
326 allometric scaling principles, basic life cycles, trophic interactions between fishes and their benthic and  
327 pelagic food resources, and fisheries [78]. When coupled with a global Earth system model to provide  
328 environmental conditions and plankton abundances as model inputs, FEISTY recreated general  
329 historical patterns of global fisheries catches [78]. The ecosystem-scale transfer efficiency values  
330 estimated by FEISTY ranged from 5-18% in oceanic, 5-27% in coastal, and 4-23% in upwelling provinces  
331 (Box 2).

332 The EcoTroph model quantifies the fraction of secondary production transferred between  
333 trophic levels using taxon-specific consumption to production rates based on life history traits [82,87],  
334 thermal habitat [82,88], and also accounts for respiration, excretion, accumulation, and transfer to  
335 detritus. Using fisheries catch data as an indicator of fish biomass by trophic level, EcoTroph estimated  
336 coastal ecosystem transfer efficiency from secondary production to trophic level 4 that varied as 5.9%  
337 in upwelling, 6.5% in tropical, 8.1% in temperate, and 10.4% in polar regions [79]. This transfer  
338 efficiency from trophic levels 2–4 increased from 7.1% to 7.6% from 1950-2010, a finding that was  
339 consistent across all coastal ecosystem types and may be explained by increased fishing exploitation  
340 [79,89]. Using sea surface temperature projections to 2100, EcoTroph projected global transfer  
341 efficiency in coastal ecosystems to decline by 0.1% until 2040 under both low and high emissions  
342 scenarios (RCP2.6 and 8.5 respectively; [79]). From 2040-2100, transfer efficiencies were projected to



343 remain stable under low emissions and decrease from 7.7% to 7.2% under high emissions – with smaller  
344 average declines in tropical ecosystems [79]. Overall, fishing pressure was positively correlated with  
345 transfer efficiency [89], while sea surface temperature was negatively correlated [79].

346

### 347 **Estimated transfer efficiencies across ocean biomes**

348 Our summary of transfer efficiency estimates indicates that it is highly variable and can range  
349 from less than 1% - 27% in upwelling regions, from 2% - 34% in temperate regions, and from 8% - 52%  
350 in tropical and subtropical regions (Box 1). This large amount of variation in transfer efficiency  
351 estimates means that fish production could vary by one order of magnitude in upwelling provinces, two  
352 orders in coastal, and up to three orders of magnitude in oceanic provinces (Box 2). Transfer efficiency  
353 has been observed to be highly variable at the ecosystem scale, influenced by ecosystem type (Box 1 &  
354 2) [90,91], trophic level [1,78], size [69], and is affected by fishing pressure [89], climate change [92-96]  
355 temperature [79,97], and varies through time [6,79,89]. Both process-level analysis and observed  
356 macroscale variations suggest that transfer efficiency increased due to fishing exploitation in the last  
357 half of the 20<sup>th</sup> century and will decline with increasing temperatures due to climate change [79].  
358 Globally, fishing exploitation has tended to target large and long-living species leading to declines in  
359 abundance compared to smaller species with faster life histories affecting transfer efficiency [98-101].  
360 These fishing-induced changes in species assemblages may have contributed to the past observed  
361 increase in transfer efficiency [79]. The large variation in transfer efficiency estimates highlights the  
362 need for more explicit consideration, rather than the tradition of relying on average values (Boxes 1,  
363 Outstanding Questions ).

364

### 365 **Concluding remarks**

366 More than 50 years after Ryther's [2] seminal paper highlighting the potential for fisheries  
367 production to be influenced by transfer efficiency variability (Boxes 1,2), it remains a key uncertainty in  
368 marine ecosystem, fisheries, and climate change research. Early observational and modelling evidence  
369 suggests that processes (e.g. metabolism, life cycle, and food web structure) and factors (e.g.  
370 ecosystem properties) influencing transfer efficiency are sensitive to environmental conditions and  
371 fisheries exploitation. Though there are key sources of uncertainty, these processes have received less  
372 research attention than other efforts to estimate future changes in temperature, primary production,  
373 and fish distribution and biomass.

374 At this stage, it is unclear if transfer efficiency is truly highly variable in space and time or if  
375 there is large measurement error around estimates. Improving transfer efficiency estimates by  
376 reducing uncertainty in empirically based estimates and more fully resolving transfer efficiency-  
377 controlling processes in predictive models is a priority for effectively anticipating changing marine  
378 resource baselines in response to climate change to avoid overexploitation (see Outstanding  
379 Questions). This may be possible as new technologies emerge that enable us to better observe  
380 biomass, productivity, and species interactions. Crucially, it is important to not limit transfer efficiency  
381 values in models, but allow the potential range of transfer efficiency to emerge from other constraints.  
382 The transfer efficiency field of research is ripe for further inquiry to build confidence in our  
383 understanding of how energy flows through marine ecosystems.

384

385 Boxes

386 **Box 1. How variable are transfer efficiency estimates and how do they vary according to biome?**

387 Summary of three studies evaluating transfer efficiency values with Ecopath with Ecosim (EwE) [77]

388 models by oceanographic biome [79,102,103]. Values from [102] were estimated from 234 published

389 EwE models. Values from [103] were estimated from the EcoTroph database of EwE models from 1950-  
 390 2010. Values from [79] were estimated from the EcoTroph database of EwE models 2000-2010.  
 391

Biome	Trophic level	Low	Mean	High
Polar/Subarctic-Boreal	2 to 3 & 3 to 4	3.5%	12.0%	25.5%
Temperate	2 to 3 & 3 to 4	1.9%	9.6%	34.4%
Tropical/Subtropical	2 to 3 & 3 to 4	0.8%	8.6%	52.0%
Upwelling	2 to 3 & 3 to 4	0.3%	8.0%	27.1%

392

### 393 Methods

394 Transfer efficiency values from [102] were extracted from the boxplot in their Figure 19. Values  
 395 for their trophic level groups III and IV, which represent transfers from trophic level 2 to 3, and trophic  
 396 level 3 to 4 respectively, were both used.

397 Transfer efficiency values from Maureaud et al. [103] reflect mean values published in the main  
 398 text. Regional minima and maxima were estimated from the table of efficiency cumulated indicator  
 399 (ECI) values by large marine ecosystem (LME) in the supplementary materials. The LME figure in [79]  
 400 was used to assign each LME to a biome and only those LMEs that were entirely of one biome type  
 401 were used. Minimum and maximum ECI per region were found over the complete time range (1950-  
 402 2010). Transfer efficiency (TE) was then calculated from ECI using:  $TE = ECI^{1/2}$ . ECI is transfer efficiency  
 403 from trophic level 2 to trophic level 4, thus these values of transfer efficiency reflect mean transfer  
 404 efficiency from trophic levels 2 to 3 and from trophic levels 3 to 4.

405 Transfer efficiency values from [79] reflect mean values published in their Figure 4a. Minima  
 406 and maxima per region were extracted from the violin plots in Figure 4a. These values of transfer

407 efficiency reflect the mean transfer efficiency from trophic levels 2 to 3 and from trophic levels 3 to 4  
 408 over the years 2000-2010.

409

410 **Box 2. How does estimated fish production vary considering variation in transfer efficiency**  
 411 **estimates?**

412 Impact of transfer efficiency variability on estimated fish production based on Ryther’s ocean provinces  
 413 [2] calculated using primary productivity and mean number of trophic levels. Observed fisheries  
 414 catches also included for reference.

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Province	Area-integrated primary production (tons organic C per year)	Mean # trophic levels	Transfer efficiency range		Estimated fish production (tonnes wet weight)		Actual catch (tonnes wet weight)
			low	high	low	high	
Oceanic	4.08E+10	6	0.05	0.18	7.82E+04	6.04E+07	8.80E+06
Coastal	9.00E+09	4	0.05	0.27	1.25E+07	1.63E+09	8.14E+07
Upwelling	2.50E+08	2.5	0.04	0.23	1.89E+07	2.55E+08	1.98E+07
Total	5.00E+10						1.10E+08

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415

416 **Methods**

417 1. Provinces were taken directly from [2]. For FEISTY model output [47] and Sea Around Us  
 418 fisheries catch data [97] they were defined as upwelling: LMEs 3, 13, 27, 29; coastal: all non-  
 419 upwelling LMEs; oceanic: the remaining ocean.

420 2. Ryther [2] had a total estimate of area-integrated primary production (APP) of  $2 \times 10^{10}$  tonnes  
 421 organic carbon per year. Modern estimates are 50 Pg carbon per year =  $5 \times 10^{16}$  g C =  $5 \times 10^{10}$

422 tonnes [104]. To update Ryther's estimates, a total of 50 Pg C was used with his proportional  
423 distribution of APP across the three provinces. These proportions were oceanic = 81.5%,  
424 coastal = 18.0%, upwelling = 0.5%.

425 3. Mean number of trophic levels equals Ryther's [2] trophic level +1 because his Table 3 listed the  
426 number of trophic levels between primary producers and human consumers, whereas the  
427 number here includes primary producers.

428 4. Low and high transfer efficiency values were the 5<sup>th</sup> and 95<sup>th</sup> percentiles of FEISTY model [78]  
429 output of TEeff\_ATL (transfer efficiency from trophic level 1 - 5) from each province, which  
430 were then converted to transfer efficiency. It is calculated as the production of all large fishes  
431 (trophic level 5) divided by the net primary production (trophic level 1) in each model grid cell. It  
432 is converted to one transfer efficiency estimate by raising to the power of 1 over the number of  
433 transfer steps (trophic level 5 – trophic level 1 = 4), TEeff\_ATL<sup>1/4</sup>.

434 5. Low and high estimates of fish production use the low and high estimates of transfer efficiency  
435 combined with the area-integrated primary production (APP) and mean number of trophic  
436 levels to calculate fish production as  $g * APP * \text{transfer efficiency}^{(\text{trophic level}-1)}$ , where  $g$  is  
437 the constant wet weight to carbon ratio of 9:1 of Pauly & Christensen [4].

438 6. Actual catch is based on global average annual reported and reconstructed catches from 2005-  
439 2014 [105] multiplied by the proportion of catch in each of Ryther's [2] provinces. The global  
440 total catch average over this 10 year time period was 110 tonnes wet weight with the following  
441 proportions: oceanic = 8%, coastal = 74%, and upwelling = 18%.

442

443 Outstanding questions

444 1. What new data acquisition methods are needed to improve transfer efficiency estimates?

- 445 2. Over what spatial and temporal scales do transfer efficiencies vary for different species and  
446 functional groups? What mechanisms explain this variation?
- 447 3. What are the impacts of reduced oxygen and increased ocean acidification on transfer  
448 efficiency?
- 449 4. How do individual level processes integrate into community level dynamics and affect transfer  
450 efficiency response to environmental change?
- 451 5. How does transfer efficiency respond to changes in species distributions that essentially create  
452 new ecosystems (i.e., new interactions, disrupted feeding patterns, differing adaptation rates)  
453 and what processes are fundamental for models to capture in order to accurately explain  
454 observed variation in transfer efficiency?  
455

456 Figures

457 Figure 1. Processes controlling transfer efficiency. A – A trophic pyramid depicts the classic view of  
458 production flowing from primary producers to secondary consumers. Roman numerals indicate trophic  
459 level. A 10% transfer efficiency of production is indicated by lighter grey in the pyramid, highlighting  
460 how little primary production gets transferred to the top of the food web. B – At the individual scale,  
461 metabolic processes determine growth efficiency. C – At the species population scale, maturation,  
462 reproduction, and survival of individual life cycles influence transfer efficiency. D – At the ecosystem  
463 scale, complex energy pathways, including the microbial loop (depicted middle left which includes  
464 dissolved organic carbon (DOC)) and differing paths through benthic and pelagic communities,  
465 influence transfer efficiency. Food web diagram after [106].

466

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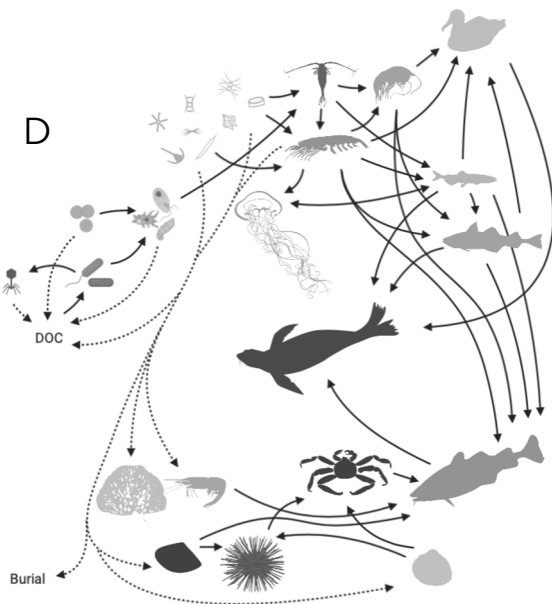
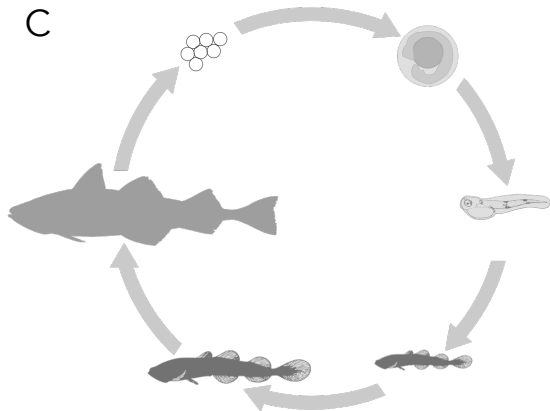
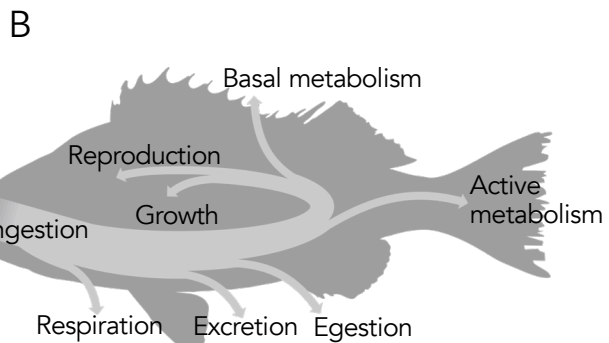
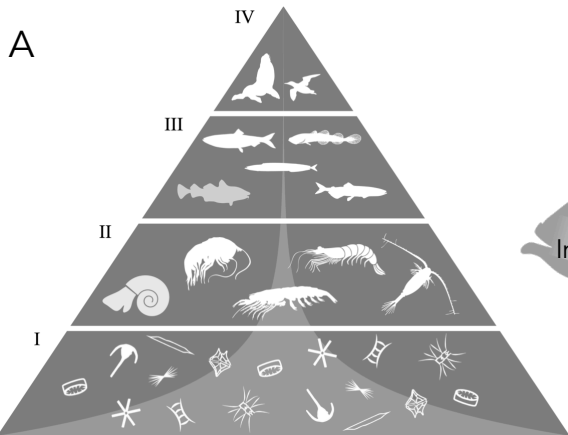
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1 Highlights

- 2 • Transfer efficiency is a key parameter describing ecosystem structure and function and is used  
3 to estimate fisheries production, however, it is also one of the most uncertain parameters.
- 4 • Questions remain about how habitats, food resources, fishing pressure, spatiotemporal scales,  
5 temperature, primary production, and other climate drivers impact transfer efficiency.
- 6 • Direct measurements of transfer efficiency are difficult, but observations of marine population  
7 abundances, diets, productivity, stable isotope analysis, and models integrating these  
8 constraints can provide transfer efficiency estimates.
- 9 • Recent estimates suggest that transfer efficiency is more variable than previously thought,  
10 compounding uncertainties in marine ecosystem predictions and projections.
- 11 • Increased understanding of factors contributing to variation in transfer efficiency will improve  
12 projections of fishing and climate change impacts on marine ecosystems.

- 1 Outstanding questions
- 2 1. What new data acquisition methods are needed to improve transfer efficiency estimates?
- 3 2. Over what spatial and temporal scales do transfer efficiencies vary for different species and
- 4 functional groups? What mechanisms explain this variation?
- 5 3. What are the impacts of reduced oxygen and increased ocean acidification on transfer
- 6 efficiency?
- 7 4. How do individual level processes integrate into community level dynamics and affect transfer
- 8 efficiency response to environmental change?
- 9 5. How does transfer efficiency respond to changes in species distributions that essentially create
- 10 new ecosystems (i.e., new interactions, disrupted feeding patterns, differing adaptation rates)
- 11 and what processes are fundamental for models to capture in order to accurately explain
- 12 observed variation in transfer efficiency?