

1 **Trait-based modelling in ecology: lessons from two decades of research**

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12 **Abstract**

13 Trait-based approaches are an alternative to species-based approaches for functionally linking individual
14 organisms with community structure and dynamics. In the trait-based approach, the focus is on the traits,
15 the physiological, morphological, or life-history characteristics, of organisms rather than their species.

16 Although used in ecological research for several decades, this approach only emerged in ecological
17 modelling about twenty years ago. We review this rise of trait-based models and trace the occasional
18 transfer of trait-based modelling concepts between terrestrial plant ecology, animal and microbial ecology,
19 and aquatic ecology. Trait-based models have a variety of purposes, such as predicting changes in species
20 distribution patterns under climate and land-use change, planning and assessing conservation
21 management, or studying invasion processes. In modelling, trait-based approaches can reduce technical
22 challenges such as computational limitations, scaling problems, and data scarcity. However, we note
23 inconsistencies in the current usage of terms in trait-based approaches and these inconsistencies must be
24 resolved if trait-based concepts are to be easily exchanged between disciplines. Specifically, future trait-
25 based models may further benefit from incorporating intraspecific trait variability and addressing more
26 complex species interactions. We also recommend expanding the combination of trait-based approaches
27 with individual-based modelling to simplify the parameterization of models, to capture plant-plant
28 interactions at the individual level, and to explain community dynamics under global change.

29

30 **Introduction**

31 Understanding community structure and dynamics is a key element of modern ecology,
32 especially in the light of global change (Harte and Shaw, 1995; Knapp, 2002). This
33 understanding was traditionally mediated by species-based approaches. More recently, such
34 approaches were complemented by approaches based on traits. Trait-based approaches are
35 popular, because they allow the direct connection of organism performance to its functions and to
36 the functions of higher levels of organization such as populations, communities and ecosystems.
37 While trait-based approaches are now firmly established in empirical research (Violle et al.,
38 2007; Suding and Goldstein, 2008), they were only introduced to modelling about twenty years
39 ago. Given that modelling is important for understanding community structure and dynamics,
40 trait-based modelling can reduce some of the challenges faced by species-based modelling. For
41 example, species-based models are usually complex, difficult to parameterize and often produce
42 outcomes that cannot be generalized to other species. Trait-based models often require less
43 parameterization effort than species-based models, facilitate scaling-up, and produce more
44 generalizable results. Here, we review the rise of trait-based models over the past twenty years,
45 highlight their main fields of application and point out avenues for future trait-based modelling.
46

47 Traits arose from the concept of plant functional groups and these groups were the first published
48 classification of organisms according to function instead of taxonomy (Raunkiaer, 1934; Grime,
49 1974). The next wave of interest into functional groups was led by the desire to predict
50 community and ecosystem responses to environmental change (Diaz and Cabido, 1997; Lavorel
51 et al., 1997; Chapin et al., 2000). The focus then shifted from functional groups to functional
52 traits and thus from species grouped because they use similar strategies to the similar
53 characteristics underlying those strategies (Yanzheng Yang et al., 2015). Distinct aspects of
54 strategies were reflected in sets of correlated traits that were defined as trait dimensions (Westoby
55 et al., 2002). This shift from a species-based approach to a trait-based approach is described as
56 the ‘Holy Grail of Ecology’ (Lavorel and Garnier, 2002). This approach involves the use of plant

57 functional traits, rather than species identities, to generalize complex community dynamics and to
58 predict the effects of environmental changes (Suding and Goldstein, 2008).

59

60 Functional traits not only help derive individual strategies (Wright et al., 2004), but also to
61 connect them to functions at organizational levels higher than those of the species such as the
62 community or ecosystem level. There are four requirements for a trait (Lavorel et al. 2007). It
63 should be connected with a function. It should be relatively easy to observe and quantify. It
64 should be possible to measure it in a standardized way across a wide range of species and
65 environmental settings. And it should have a consistent ranking. Trait-based ecology is further
66 based on the assumption that trade-offs and constraints have shaped phenotypic variation in
67 different trait dimensions (Messier et al., 2017).

68

69 Sets of plant traits that reliably represent the processes of growth, survival, and reproduction
70 (Violle et al., 2007) make it possible to facilitate and generalize empirical and modelling studies.
71 Therefore, researchers attempted to define a universal set of traits. Pачepsky et al. (2001)
72 identified twelve critical traits that affected resource uptake, the area over which resource is
73 captured, the internal allocation of resources between structure, storage and reproduction, time of
74 reproduction, number of progeny produced, dispersal of progeny, and survival. Other researchers
75 used smaller numbers of traits. The leaf economics spectrum, for example contains only six
76 (Wright et al., 2004). Díaz et al. (2015) also used six traits but not those of the leaf economics
77 spectrum, and several researchers even used a set with as few as three traits (Westoby, 1998;
78 Westoby et al., 2002; Wright et al., 2004; Chave et al., 2009; Garnier and Navas, 2012). Thus,
79 rather than applying a universal trait set, modern use of the concept implies a selection of a small
80 set of critical functional traits specific to the needs of a specific study and dependent on the
81 specific organisms for which strategies are being described.

82

83 Using trait-based approaches overcomes some of the well-known problems of species-based
84 approaches. In trait-based approaches, for example, it is possible to directly connect community
85 functions such as production to environmental changes via functional traits. Moreover, the trait-
86 based approach is an intuitive approach for addressing evolutionary processes because evolution
87 selects organisms in a community according to their function and not their taxonomy. Trait-based

88 approaches are, furthermore, more suitable than species-based approaches for generalizations
89 across species as they are not tied to taxonomy. In addition, trait data are, in most cases, more
90 readily available than species data due to the rapid expansion of trait databases. Trait databases
91 are especially well developed for plants (Kleyer et al., 2008; Kattge et al., 2011).

92

93 Although current trait-based approaches have several benefits, they also have some shortcomings
94 not present in species-based approaches. One of these is the choice of appropriate functional traits
95 and their trade-offs with other traits given that a great diversity of traits are available (Funk et al.,
96 2017). Furthermore, traits differ intraspecifically but these differences are often neglected (Violle
97 et al., 2012; Bolnick et al., 2011). Existing trait databases are usually of limited use when it
98 comes to species interactions, intraspecific trait variation and variable environmental settings
99 (Funk et al., 2017). In addition, the theoretical assumptions of trait-based studies are not always
100 supported by experimental data (Suding and Goldstein, 2008). These shortcomings can be
101 overcome by closer cooperation between empirical and theoretical researchers and by the
102 development of standards for trait data collection (e.g. Garnier and Shipley, 2001; Pérez-
103 Harguindeguy et al., 2013).

104

105 In the most recent 20 years trait-based approaches have entered ecological modelling. The main
106 advantage of modelling over empirical approaches is that it allows the comparison of several
107 scenarios with different sets of assumptions, so conducting virtual experiments. This makes
108 possible the systematic exploration of the outcomes under each set of assumptions and the
109 elucidation of the mechanisms underlying the patterns observed. Using models therefore avoids
110 the costs and risks of real-world experiments. In principal, trait-based models consist of
111 combinations of functional traits that respond to environmental changes (response traits) and
112 affect community and ecosystem properties (effect traits) (Fig. 1). Implementing trait-based
113 approaches for modelling may also help overcome the high data demand of species-based models
114 (Garrard et al., 2013; Weiss et al., 2014), simply due to the fact that traits usually represent more
115 than one species. For the same reason, trait-based modelling may also reduce computing times.
116 Moreover, using traits in modelling can facilitate scaling of physiological processes to global

117 scales (Shipley, Vile, & Garnier, 2006; Lamarque et al., 2014) because traits can function as a
 118 common currency across scales in these models.

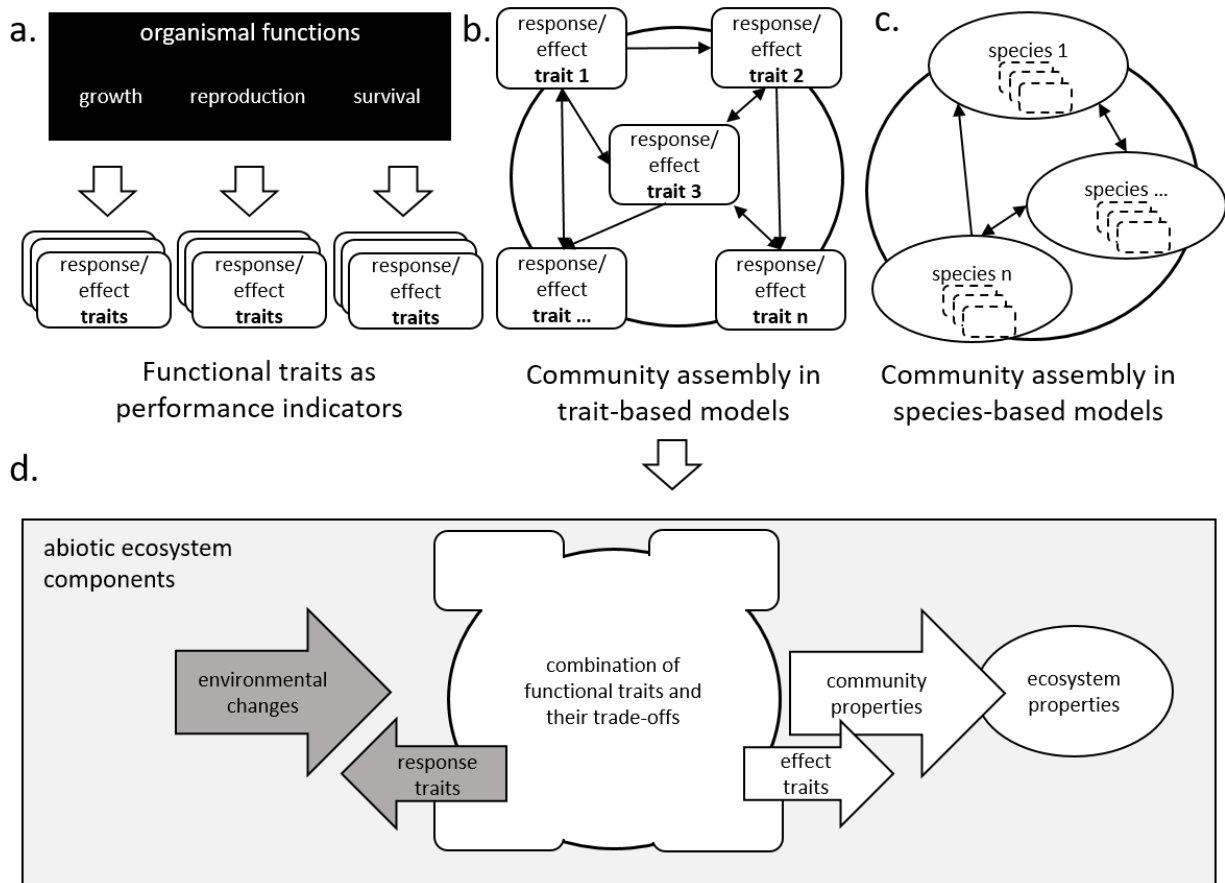


Fig. 1. Conceptual overview of trait-based models compared to species-based models. Functional response and effect traits (rounded rectangles) are performance indicators that are related to organismal functions (a). Trait-based models represent community (circle) assembly by interacting functional response and effect traits (b). Species-based models represent community assembly by interacting species that may implicitly contain traits (c). Trait-based models can be divided into models that use functional traits only as static inputs (white elements in d) that affect community and ecosystem properties and models that use functional traits both as inputs and dynamic outputs (white and grey elements in d). Response traits change dynamically depending on changing environmental conditions.

119

120 Given the advantages of trait-based approaches, it is still surprising that their incorporation into
 121 the tool-kit of ecological modelling has been slow and that they are applied in proportionally
 122 fewer cases of modelling than of empirical work. In this paper, our aim is to systematically

123 review applications of trait-based models in ecology. More specifically, we 1) discuss definitions
124 and terminology of trait-based approaches, 2) evaluate how trait-based models are used in
125 different disciplines, and 3) identify avenues for the future implementation of trait-based models,
126 including cross-discipline exchange. The trait-based modelling applications in this review
127 contribute to identifying principles that underlie spatiotemporal community dynamics, exploring
128 species distributions, investigating species interactions, scaling ecosystem processes from
129 individual traits to ecosystem functioning, explaining the consequences of climate and land-use
130 changes for community dynamics, and also supporting conservation and invasion studies.

131

132 **Methods**

133 This paper is based on a systematic literature review. We searched for papers using a topic search
134 on the “Web of Science Core collection”. We first used the search term “trait-base*” AND
135 model* and in a second search “traitbase*” AND model*. The first search yielded 772 papers all
136 of which turned out to postdate 1978. The second search added 4 papers, which were from the
137 period 2010-2018. We excluded all papers from obviously irrelevant fields, such as psychology,
138 medicine, engineering, business, management, history, industrial relations, linguistics, education,
139 nutrition, and biotechnology (Supplementary Material. Tab. 2). After this filtering of both
140 searches, we retained 623 papers that focused on ecology and related biological sciences. These
141 ecological and biological publications were the most recent among all the papers we found (Fig.
142 2). In addition to the publications found during this systematic literature search, we also included
143 papers discovered by the snowball principle, i.e. the papers cited in papers already selected. We
144 also included additional publications recommended by experts in the field. We finalized our
145 research by selecting only those papers from our compilation that directly addressed concrete
146 trait-based models. We excluded pure genetics, toxicology, climate and evolution studies,
147 because we wanted to focus on ecological studies. We did not consider studies that focused on
148 statistical analysis of empirical data, but we did include statistical models if the focus was on the
149 model such as in species distribution modelling. Our focus was on primary modelling papers, so
150 that we only referred to secondary modelling papers that discuss, use, extend or review
151 previously published models when they introduce a new trait-based perspective. We did not
152 consider editorial material or technical software descriptions. This procedure yielded 188 papers
153 (Supplementary Material. Tab. 1, Fig. 2).

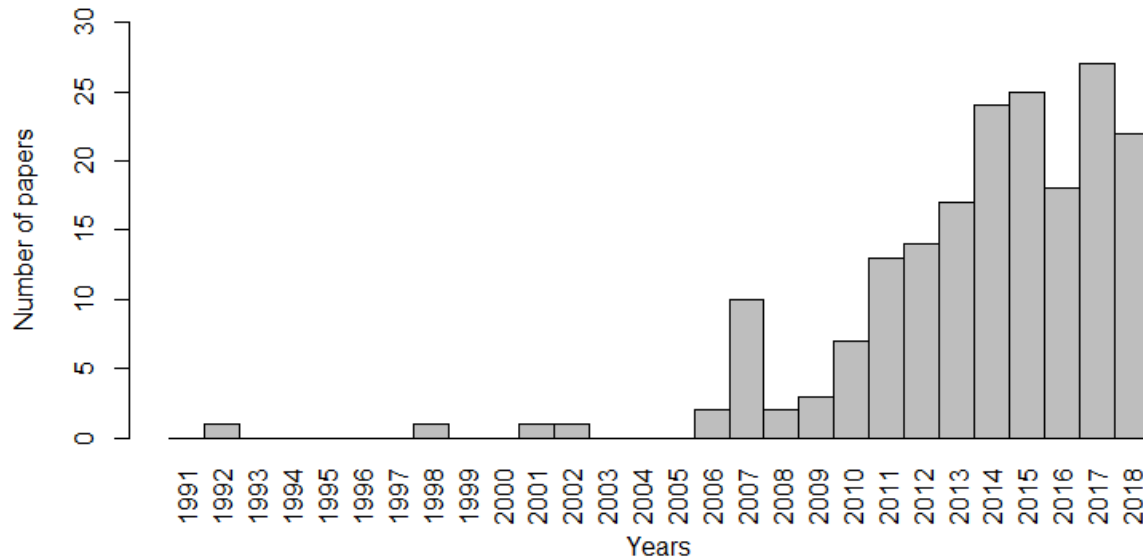


Fig 2. Papers on trait-based models included in the final list of the reviewed model (Supplementary Material. Tab. 1).

155 Glossary

156

157 **Functional traits** well-defined morpho-physio-phenological characteristics of individual organisms that relate to the
 158 patterns of growth, reproduction, and survival of the species (McGill et al., 2006; Violle et al., 2007), and that
 159 evolved in response to abiotic environmental conditions and interactions with other species (Reich et al., 2003; Clark
 160 et al., 2012).

161 **Hard traits** those directly related to important physiological processes that define the growth, reproduction and
 162 survival of an organism. Hard traits are usually hard to measure, and therefore in practice they are identified and
 163 measured on the basis of surrogate **soft traits** (Hodgson et al., 1999) that are correlated with hard traits but are more
 164 easily or cheaply measured.

165 **Response traits** determine how a species reacts to a disturbance or a change in abiotic or biotic processes in its
 166 environment (Lavorel et al., 1997; Lavorel and Garnier, 2002).

167 **Effect traits** determine how a species influences ecosystem properties (Lavorel et al., 1997; Lavorel and Garnier,
 168 2002). Effect traits alter abiotic and biotic processes corresponding to a wide range of ecosystem functions (Eviner
 169 and Chapin III, 2003).

170 **Plant functional types (PFT)** Groups of species with presumably similar roles in ecosystem functioning (Lavorel et

171 al., 1997). They are considered as an important ecological framework for describing the mechanisms underlying
172 vegetation responses (McIntyre et al., 1995; Pausas, 1999).

173 **Community-weighted mean (CWM) traits** Quantification and use of aggregated trait attributes of the community
174 as a measure of diversity that does not take species into account. To calculate a community aggregated trait value,
175 relative abundances of species and their trait values are used (Violle et al., 2007; Funk et al., 2016).

176 **Intraspecific trait variability (variation)** is the difference in the values of functional traits within one species that
177 results from the development and adaptation of species to environmental change (Albert et al., 2011; Schirpke et al.,
178 2017). There are two sources for this variation. One is heritable differences between individuals and the other
179 phenotypic plasticity in trait values across different environmental conditions (Moran et al., 2016).

180 **Conceptual models** models that are not implemented in equations or programming code. In practice, they are
181 usually a graphical representation of causal relationships (or flows) between factors or processes.

182 **Statistical models** descriptive mathematical models of relationships between variables based on assumptions about
183 the data sampled. They represent a set of probability distributions on the sample space (Cox et al., 1979).

184 **Equation-based models** mathematical models that are formulated as a set of ordinary differential equations, partial
185 differential equations, or integro-differential equations. They can be solved analytically or numerically. These
186 models are sometimes also called **mechanistic models**, **physiological models** or **process-based models**, although
187 each of these terms is also used for non-equation-based models. For instance, process-based models are based on a
188 theoretical understanding of the relevant ecological processes. They are built on explicit assumptions about how a
189 system works, and these models are especially well-designed to predict the effects of global change (Cuddington et
190 al., 2013). **Dynamic Global Vegetation Models (DGVMs)** and **Earth System Models (ESM)** also fall in this
191 category.

192 **Individual-based models** (or **agent-based models**) explicitly consider individual organisms as objects with
193 characteristics (traits) that influence interactions with other individuals and the environment (Grimm and Railsback,
194 2005). They adopt a bottom-up approach where population-level behavior emerges from these individual interactions
195 (DeAngelis and Grimm, 2014). Individual-based models are usually not based on equations, but on rules
196 implemented in programming code. Individual-based models are highly suitable for spatially explicit
197 implementations (Grimm et al., 2005), often combined with a **grid-based modelling** approach.

198

199 *Types and scales of trait-based models*

200 We classified the papers discovered in our systematic search according to model type and target
201 scale. For model type, we distinguished between conceptual models, statistical models, equation-
202 based models, individual-based models, and their combinations (see Glossary and Supplementary
203 Material. Tab. 1). Statistical models occurred in 26% of the reviewed papers and equation-based
204 models in 60-61%. Together they were the most common types in trait-based modelling.

205 Conceptual models are probably more common than was reflected in the papers we examined

206 (5% of the reviewed papers) because they often precede a mathematical or code-based model
207 formulation. Individual-based models represented 16% of the reviewed papers.

208

209 Trait-based models address questions at local to landscape and global scales (Supplementary
210 Material. Tab. 1) and at the organizational level of individuals, species, populations,
211 communities, and ecosystems. Where the models targeted the ecosystem level, they were
212 implemented as equation-based models. This is probably due to the fact that ecosystem-level
213 models focus on matter or energy fluxes and individual-based models are not suitable for
214 modelling fluxes. However, models at the species, population or community level do not usually
215 consider fluxes but use organisms as their inputs. This is typical of individual-based models but
216 all other model types are also used at species, population, and community levels. Models of
217 processes at the level of individual organisms or their organs were either implemented as
218 statistical models of plant growth or, when emphasizing physiological mechanisms, as equation-
219 based models.

220

221 Overall, different model types benefit in different ways from the integration of traits depending
222 on the target scale of the question addressed by the model. In the following sections, we present
223 studies that illustrate the potential benefits of using trait-based modelling for various scales and
224 model types to study plants and animals in terrestrial and aquatic ecosystems, microbial
225 organisms, and soil decomposers.

226

227 **1. Trait-based modelling of plants in terrestrial ecosystems**

228 Trait-based approaches were originally developed and discussed for plants in terrestrial
229 ecosystems. This focus on plant sciences was mirrored in the trait-based modelling studies. Fifty
230 percent of all studies in this review addressed terrestrial vegetation (note that we discuss the two
231 studies on fungi in our review as part of this section). The aims of trait-based vegetation models
232 were diverse. They covered investigations of plant growth and interactions, species distributions,
233 plant invasiveness, community assembly and dynamics, biodiversity hypotheses, ecosystem
234 services, and global vegetation patterns and dynamics (Fig. 3).

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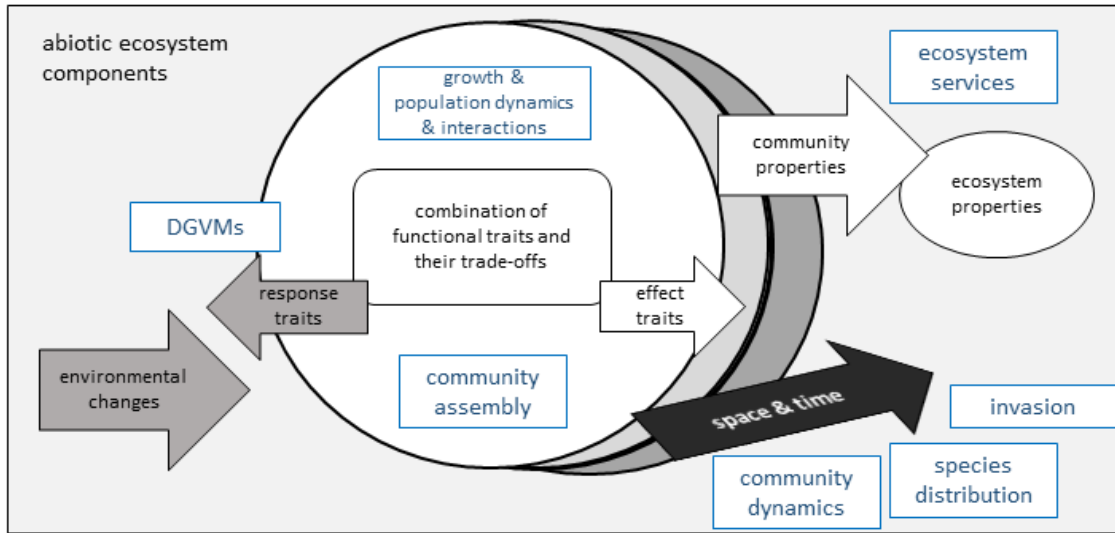


Fig. 3. Overview of the models of plants in terrestrial ecosystems based on their main purposes and research questions (rectangles with blue edges). Large circles represent community development in space and time (see Fig. 1 for further explanation).

236

237 1.1. Trait-based models on plant growth, population dynamics, and interactions

238 Plant growth, population dynamics, and interactions were modelled with a range of model types,
 239 including statistical, equation-based and individual-based models (Supplementary Material. Tab.
 240 1). The influence of traits on the growth of individual plants or plant organs was most commonly
 241 addressed using statistical models. These statistical models were either non-linear regression
 242 models (Chavana-Bryant et al., 2017), Bayesian approaches, or both (Héroult et al., 2011; Aubry-
 243 Kientz et al., 2015; Thomas and Vesk, 2017a; Thomas and Vesk, 2017b). Equation-based
 244 approaches focused on mechanisms such as carbon and biomass fluxes within and across plants
 245 (Enquist et al., 2007; Sterck and Schieving, 2011), water uptake (Fort et al., 2017) or on the
 246 physiological processes producing salt tolerance (Paleari et al., 2017).

247

248 Both models on plant population dynamics in our review were equation-based models. One study
 249 investigated the influence of considering whole life cycles in fitness assessments (Adler et al.,
 250 2014), and the other one studied the population dynamics and viability of a primrose (and a lizard)
 251 population (Jaffré and Le Galliard, 2016). Comparing the results from the equation-based integral
 252 projection model with those from an analogous individual-based model, Jaffré and Le Galliard
 253 (2016) highlighted the importance of constructing individual-based models when very small

254 populations are investigated. Our review confirms the conclusion of Salguero-Gómez et al. (2018)
255 that trait-based approaches are still underrepresented in studies of population dynamics. However,
256 note that such combinations of trait-based and demographic approaches are more common for
257 aquatic organisms (Vindenes et al., 2014; O'Farrell et al., 2015) or terrestrial mammals (Santini et
258 al., 2016; Jaffré and Le Galliard, 2016; van Benthem et al., 2017) than for plants.

259

260 Interactions such as competition have mainly been studied with equation- and individual-based
261 models or their combination. Using dynamic process-based models, Ali et al. (2013) and Ali et
262 al. (2015) contrasted two alternative competition theories and demonstrated how elevated carbon
263 dioxide concentration influences plant competition and, consequently, community composition in
264 an ecosystem. In a combined equation- and individual-based approach, Fyllas et al. (2014)
265 simulated ecosystem fluxes based on two axes: the leaf economics spectrum (Wright et al., 2004)
266 and tree architecture spectrums (Chave et al., 2005; Mori et al., 2010). Individual-based models
267 are particularly useful for representing plant interactions because it is the individual level at
268 which interactions are initiated. For example, Taubert et al. (2012) used them to investigate
269 biofuel production in grasslands of temperate regions. In this model, above- and below-ground
270 plant functional traits were used to characterize how successful plants were in taking up resources
271 and competing with neighbors.

272

273 Based on these examples and the nature of the models, we suggest that different kinds of models
274 have different efficiencies in the sense of producing good results without requiring large amounts
275 of data. Statistical models are most efficient for describing the relationship between traits and
276 plant growth but equation-based models are most efficient for describing mechanisms, simple
277 interactions, or ecosystem fluxes. Individual-based models are the best choice, however, for
278 complex trait-based interactions. This is because individuals are the nexus of trait-based
279 interactions.

280

281 *1.2. Trait-based models on species distributions*

282 Although trait-based modelling was often applied as an alternative to species-based approaches, a
283 number of trait-based modelling papers were devoted to questions related to species distribution.
284 For example, a combination of species distribution models and trait-based approaches was

285 explicitly recommended to estimate the impact of climate change on species (Willis et al., 2015).

286

287 The great majority of the studies on species distribution modelling combined a trait-based
288 approach with statistical modelling, often by using a Bayesian approach (Supplementary
289 Material. Tab. 1). For example, Powney et al. (2014) showed that predictions of trait-based
290 species distribution models were best for broad-scale changes in regions with similar land-cover
291 composition. In another example, a new application of time-to-detection modelling was able to
292 detect multiple species as a function of plant morphological and phenological traits (Garrard et
293 al., 2013). The model by Rosenfield and Müller (2017) estimated the relative abundances of
294 species that meet the values of functional traits found in a target ecosystem.

295

296 Trait-based models provide some advantages when predicting local community assembly,
297 especially where environmental filtering and niche differentiation shape communities. Among the
298 algorithms used in the papers on trait-based models, Maxent (e.g. Shipley et al., 2011; Sonnier et
299 al., 2010) and the TraitSpace model (e.g. Laughlin et al., 2012; Laughlin et al., 2015; Laughlin
300 and Joshi, 2015) were used for trait-based environmental filtering. These algorithms predict low
301 probabilities for any species whose trait distribution fails to pass through the environmental filter
302 (Laughlin and Laughlin, 2013). The Maxent model and the TraitSpace model differ in their ability
303 to predict the relative abundance of species from a regional species pool (Laughlin and Laughlin,
304 2013). Maxent predictions are degraded when high intraspecific variability is included (Merow et
305 al., 2011). The importance of intraspecific variation in functional traits was underlined by Violle
306 et al. (2012); Read et al. (2017) who found that intraspecific variability compensated for the
307 effects of interspecific variation along a climatic gradient. Moreover, trait-based models are not
308 only inaccurate when intraspecific variability is ignored but also when environmental changes are
309 rapid. Therefore, when the environment changes rapidly, trait-based models become inaccurate
310 because the traits measured were selected for by a previous, different, environment (Welsh et al.,
311 2016). A statistical approach uniting trait-based and species distribution models was also applied
312 to model the distribution of wood-inhabiting fungi (Abrego et al., 2017). Finally, the only
313 equation-based model in this section was a model that incorporated plant physiology to predict
314 tree distributions along resource gradients (Sterck et al., 2014).

315

316 Thus, trait-based approaches are useful for modelling species distributions. Current efforts in
317 trait-based species distribution modelling focus on moving from mean trait values to intraspecific
318 trait variability, e.g. by implementing a Bayesian framework (Laughlin et al., 2012).

319

320 *1.3. Trait-based models of community assembly*

321 Community assembly results from species sorting by environmental filters and biotic
322 interactions. Until now, trait-based models of community assembly used mainly statistical
323 modelling and equation-based approaches to capture this process (Supplementary Material. Table
324 1). We further found one individual-based model [(Pachepsky et al., 2007) based on a model by
325 Bown et al. (2007) mentioned in section 1.1. Trait-based models on plant growth, population
326 dynamics, and interactions], and three conceptual models (Bhaskar et al., 2014; Crowther et al.,
327 2014; Losapio and Schöb, 2017), including one on fungal community assembly (Crowther et al.,
328 2014). The group of models of community assembly partially overlapped with models of species
329 distribution and was thus already partly discussed in section 1.2. Trait-based models on species
330 distributions. Three groups of studies emerged: First, a large group of publications where the
331 intention was to identify traits that affect community assembly; second, a group of four papers
332 studying intraspecific trait variability (Pachepsky et al., 2007; Laughlin et al., 2012; Yang et al.,
333 2015; Schliep et al., 2018) ; and, third, another group of three papers where traits were used as
334 response traits to distinguish between biotic and abiotic filtering (Bhaskar et al., 2014; Chauvet et
335 al., 2017) and to assess effects of environmental change (Losapio and Schöb, 2017).

336

337 The majority of the models reviewed in the current section were in the first group that aimed to
338 distinguish traits that influence species abundance, richness and functional diversity. One case
339 study, for instance, indicated that seed production and dispersion traits are important for regional
340 species abundance (Marteinsdóttir, 2014). In another case study, a trait-based model incorporated
341 both neutral theory and niche theory to identify whether, and which, plant traits determine
342 community assembly and biodiversity patterns, including plant species richness and abundance,
343 across environments (Shipley et al., 2006). To unify classic coexistence theory and evolutionary
344 biology with recent trait-based approaches, Laughlin et al. (2012) incorporated intraspecific trait
345 variation into a set of trait-based community assembly models. These models generate species
346 abundances to test theories about which traits, which trait values, and which species assemblages

347 are most effective for achieving a specified functional diversity. Larson and Funk (2016)
348 advocated for including regeneration traits in a model of community assembly.
349 A few statistical trait-based models in the first group aimed at quantifying the relationship
350 between environmental gradients and individual-level traits or community-weighted mean traits
351 to describe environmental filters (Laughlin et al. 2015). The common assumption of such models
352 was that traits are unimodally distributed and centered on an optimal trait value in any given
353 environment. In contrast, an extended Traitspace model (Laughlin et al., 2015) adopting a
354 hierarchical Bayesian approach (Laughlin et al., 2012) captured multimodal trait distributions.
355 Improving the Traitspace model in this way increases the power of trait-based predictions of
356 species abundances. The power increase arises because the prediction of species abundance
357 distributions then reflects the true functional diversity of a community. These community
358 assembly models were also used to test the mass ratio hypothesis (Laughlin, 2011; Laughlin,
359 2014) and to refine restoration objectives, either by manipulating abundances of species already
360 existing in the system or by adding species from warmer climates to the local species pool
361 (Laughlin et al., 2017). Similar to models on species distribution, the MaxEnt algorithm is also
362 used for models of community assembly to predict the effect of trait-based environmental
363 filtering on the species pool, for example, in forest community assembly (Laughlin et al., 2011)
364 or using the community assembly via trait selection approach (CATS) (Laliberté et al., 2012;
365 Frenette-Dussault et al., 2013).

366

367 Equation-based models in the first group tended more towards theoretical questions: For
368 example, they investigated the multidimensional nature of species coexistence based on traits
369 (Kraft et al., 2015), they implemented biophysical principles to test niche vs neutral processes
370 (Sterck et al., 2011); or they showed that self-limitation promotes rarity (Yenni et al., 2012).

371

372 Thus, it is possible to use trait-based community assembly models for tackling questions of
373 fundamental and applied ecology. To be optimally effective, more of such models should
374 incorporate multimodal trait distributions and intraspecific trait variability.

375

376 *1.4. Trait-based models of community dynamics*

377 Trait-based modelling can be helpful for explaining not only static community assembly but also
378 the temporal and spatial dynamics of communities. We found twice as many equation-based
379 models of community dynamics as individual-based models (Supplementary Material. Tab. 1).
380 The equation-based approaches included basic and applied research. Among the basic research,
381 two studies investigated vegetation dynamics at the landscape level (Falster et al., 2011; Quétier
382 et al., 2011), one study quantified environmental filtering and immigration rates of new species
383 (Jabot, 2010), and one study assessed plant community stability considering litter decomposition
384 (Miki and Kondoh, 2002). Among the more applied research, three studies included the effect of
385 environmental change: Moor (2017) studied the relationship between dispersal and species
386 diversity along a climate warming gradient; Savage et al. (2007) investigated overyielding and
387 other responses to environmental change; and Tanaka (2012) advanced Savage et al.'s (2007)
388 study by considering interspecific competition and trait covariance structure. One further
389 equation-based model with an applied question was developed to compare the effect of different
390 cropping systems on weed traits (Colbach et al., 2014).

391

392 The individual-based models in this section targeted effects of regional processes on grasslands
393 (Weiss et al., 2014), as well as the processes of grazing and disturbances. The effects of grazing
394 on a grassland community were investigated in two individual- and trait-based models (May et
395 al., 2009; Weiss and Jeltsch, 2015). The results of these models indicated that trait size symmetry
396 of competition is central for community dynamics. This indication arose from the model only
397 generating the patterns predicted by the grazing reversal hypothesis under specific conditions.
398 These conditions were the explicit inclusion in the model of shoot and root competition, and the
399 assumptions that plants with larger aboveground parts were superior competitors and
400 belowground competition was consistently symmetrical. A similar functional group scheme
401 based on four key traits representing typical species responses to disturbance was used in an
402 individual-based model that led to the conclusion that the competition-colonization trade-off is
403 insufficient to predict community dynamics (Seifan et al., 2012; Seifan et al., 2013). Thus, trait-
404 based approaches have great potential in community dynamics modelling. This is especially true
405 where it is important to include spatial interactions because these are often mediated by traits.

406

407 *1.5. Trait-based dynamic global vegetation models (DGVMs)*

408 Beyond the community and ecosystem levels mentioned in previous sections, global vegetation
409 classification is possible with DGVMs. More specifically, DGVMs advance understanding of the
410 distribution of plant functional types across spatial scales (Prentice et al., 2004). DGVMs are
411 used as precursors of, or parts of, earth system models in which they represent energy, carbon and
412 water fluxes (Scheiter et al., 2013; Drewniak and Gonzalez-Meler, 2017). Dynamic vegetation
413 classification is enabled by calculating separately ecosystem fluxes and plant functional type
414 occurrences both of which can be based on traits. DGVMs are mainly or entirely equation-based
415 models because this form allows them to adequately represent ecophysiological processes
416 (Supplementary Material. Tab. 1). More recent DGVMs have added individual-based
417 components to account for individual variation (Scheiter et al., 2013).

418

419 Most DGVMs were used to investigate vegetation responses to current climate and climate
420 change (e.g. Verheijen et al., 2013; Sakschewski et al., 2015). Walker et al. (2017) applied the
421 Sheffield DGVM (Woodward and Lomas 2004) to compare the predictive power of four trait-
422 scaling hypotheses on the distribution of global maximum rate of carboxylation. The four
423 hypotheses used were those on plant functional type, nutrient limitation, environmental filtering,
424 and plant plasticity. The result of this comparison showed that nutrient limitation was the most
425 probable driver of global maximum rate of carboxylation distributions. DGVMs are criticized for
426 being insufficient realistic. This insufficiency arises because they use plant functional types with
427 constant attributes and do not represent competitive interactions (Scheiter et al., 2013). This
428 criticism led to a stronger focus on traits and to the addition of individual-based modules (Harper
429 et al., 2016). The Jena Diversity-DGVM incorporates 15 traits with several functional trade-offs
430 that defined plant growth strategies (Pavlick et al., 2012). These functional properties of the
431 vegetation were derived, unlike in standard DGVMs, from mechanistic trait filtering via
432 environmental selection. The Jena Diversity-DGVM also demonstrated its advantages over
433 bioclimatic approaches (Reu et al., 2010; Reu et al., 2011). Instead of plant functional types, the
434 adaptive DGVM of Scheiter and Higgins (2009) and Scheiter et al. (2013) was based on traits.
435 The novelty of this adaptive DGVM lay in the process-based and adaptive modules for
436 phenology, carbon allocation and fire within an individual-based framework. This allowed the
437 vegetation component in the model to adapt to changing environmental conditions and

438 disturbances. Such adaption is not possible in models based on static functional types.

439

440 As our review demonstrates, DGVMs provide a good example of the shift from plant functional
441 types towards functional traits (Yang et al., 2015) (e.g. compare Smith et al. (2001) and
442 Holzwarth et al. (2015)). Moreover, individual-based modelling is increasingly applied to
443 represent individual interactions and foster the dynamic nature of DGVMs.

444

445 *1.6.Trait-based models of plant invasions*

446 Trait-based modelling was frequently used to study invasion (Supplementary Material. Tab. 1).

447 The frequency of this use probably arises because it is a common goal of invasion biology to

448 identify traits that can be used to predict future invaders. This goal was particularly common

449 among statistical models (Otfinowski et al., 2007; Herron et al., 2007; Küster et al., 2008). The

450 individual-based models of plant invasion focused on understanding the invasion process

451 incorporating, for instance, disturbance (Higgins and Richardson, 1998), or herbivory (Radny and

452 Meyer, 2018). These models have different regional and taxonomic foci including pine trees in

453 the southern hemisphere (Higgins and Richardson, 1998), exotic plants in North America

454 (Otfinowski et al., 2007; Herron et al., 2007), invasion success in Germany (Küster et al., 2008),

455 and establishment success as the combined effect of functional traits and biotic pressures (Radny

456 and Meyer, 2018).

457

458 However, these models have yet to yield a universal set of traits that characterize potentially

459 invasive species. Future trait-based invasion models should address all the processes and

460 interactions relevant to the system being studied. This might be facilitated by individual-based

461 modelling approaches.

462

463 *1.7.Trait-based models of ecosystem services*

464 Ecosystem service models are usually built with a management goal. Thus, they benefit from

465 including plant functional traits because functional traits are aggregate measures that can more

466 easily be targeted by ecosystem management than species. Most models in this section were

467 statistical models (Supplementary Material. Tab. 1), often in the form of generalized linear

468 models (Diaz et al., 2007; Lavorel et al., 2011), whereas three models were equation-based.
469 According to Lavorel et al. (2011), ecosystem properties were better captured by models
470 including spatial variation in environmental variables and plant traits than by land-use models.
471 Variation across the landscape in the community-weighted mean of four traits and their
472 functional divergence were modelled with generalized linear models (Lavorel et al., 2011).
473 Compared to remote sensing, this trait-based statistical modelling approach better reflected the
474 process of land use that underlay ecosystem properties (Homolova et al., 2014). Another model
475 investigated the influence of plant and microbial functional traits on grassland ecosystem services
476 (Grigulis et al., 2013). Based on Lavorel et al. (2011) and Grigulis et al. (2013), future ecosystem
477 services were estimated for three socio-economic scenarios (Schirpke et al., 2017). The approach
478 demonstrated that ecosystem services were potentially highly resilient. In two other
479 semimechanistic models, functional traits facilitated the scaling-up of well-understood functional
480 trade-offs from the organismal to the ecosystem level (Lamarque et al., 2014).

481

482 Equation-based models of ecosystem services ranged from assessing the sensitivity of ecosystem
483 services to land-use change (Quétier et al., 2007), determining the vulnerability of pollination
484 services (Astegiano et al., 2015), and evaluating the management of mown subalpine grasslands
485 (Lochon et al., 2018).

486

487 Based on the examples in this section, trait-based models demonstrate great potential for solving
488 applied questions in ecosystem studies as well as for those involving scaling.

489

490 *1.8. Trait-based models on interactions between plants and other organisms*

491 A few trait-based models did not focus purely on vegetation and interactions among plants but
492 also included the interactions of plants with other groups of organisms. These models were partly
493 conceptual and partly equation-based (Supplementary Material. Tab. 1). For example, the effects
494 of biodiversity on multispecies interactions and cross-trophic functions were described in a trait-
495 based bottom-up framework (Lavorel et al., 2013). This conceptual model was linked to a
496 statistical structural equation model which demonstrated that high functional and interaction
497 diversity of animal mutualists promoted the provisioning and stability of ecosystem functions. In

498 another case study, avian body size was identified as an important response trait related to the
499 susceptibility of avian seed dispersers to disturbance by humans (Schleuning et al., 2015). A
500 conceptual model (Pöyry et al. 2017) reconstructed how the effects of soil eutrophication cascade
501 to higher trophic levels across a range of plant-herbivore interactions. The model was evaluated
502 based on butterfly and moth data. The authors suggested that a major future trend will be the
503 increased dominance of insect species that are large, dispersive dietary generalists over those
504 preferring oligotrophic environments. These conceptual models await further testing by being
505 converted into equation- or code-based models and the empirical testing of the predictions of
506 these models.

507

508 There were also four equation-based models in this section addressing nutrient competition in an
509 earth system model (Zhu et al., 2016), trade-offs of defensive plant traits in plant-herbivore
510 interactions (Mortensen et al., 2018), plant-soil feedback mediated by litter and microorganisms
511 (Ke et al., 2015), and three-way interactions between a plant, a herbivore and a beneficial
512 microbe in the context of biological invasions (Jack et al., 2017).

513

514 **2. Trait-based modelling of animals in terrestrial ecosystems**

515 Animals are underrepresented among papers on the trait-based modelling of terrestrial
516 ecosystems, whereas trait-based models of marine ecosystems which included animals abounded.
517 There are about three times as many marine as terrestrial papers including animals in our review
518 (see section 3. Trait-based modelling in aquatic ecosystems). The reason for the imbalance may
519 lie in there being many different behaviours, feeding strategies and morphologies among
520 terrestrial animals (Scherer et al., 2016), making it hard to define common functional traits.
521 Nevertheless, 23 papers covered trait-based modelling of animals in terrestrial ecosystems. There
522 were twice as many equation-based models as individual-based models and almost as many
523 statistical models as equation-based ones (Supplementary Material. Tab. 1). As the following
524 studies show, these models cover a broad range of topics, including population dynamics and

525 survival analysis, predator-prey and host-pathogen interactions, species distributions, and
526 community assembly.

527

528 Population dynamics was more frequently investigated in trait-based modelling studies of
529 animals than plants in terrestrial ecosystems. We included here pure population dynamics studies,
530 but also other studies at the population level, namely time-to-detection studies, survival analysis,
531 vulnerability analysis, home range determination, and a study of eco-evolutionary dynamics. For
532 example, the effect of functional traits on the population dynamics of mites was studied with
533 equation-based integral projection models (Smallegange and Ens, 2018), drawing on the dynamic
534 energy budget theory better known from aquatic studies (see section 3. Trait-based modelling in
535 aquatic ecosystems). According to an individual-based model, the population dynamics of
536 meerkats depend on intraspecific variation in body mass (Ozgul et al., 2014). In a similar but
537 equation-based model trait-demography relationships were studied to identify the mechanism
538 underlying population fluctuations (van Benthem et al., 2017). Trait-based models of population
539 dynamics investigated the responses of populations to environmental changes (Santini et al.,
540 2016) and to perturbations (Ozgul et al., 2012). Using an approach similar to that of the time-to-
541 detection studies mentioned in section 1.2 (Trait-based models of species distributions),
542 Schlossberg et al. (2018) modelled detectability for ten mammal species. This model was based
543 on species traits such as body mass, mean herd size and color and employed a statistical approach
544 based on conditional likelihoods. An example of a trait-based survival model was the prediction
545 of bat survival based on reproductive, feeding, and demographic traits such as age, sex, and type
546 of foraging (Lentini et al., 2015). A trait-based vulnerability index was applied to subarctic and
547 arctic breeding birds in a statistical model constructed around MaxEnt and CATs (Hof et al.,
548 2017). We found three further individual-based models: Scherer et al. (2016) explored the
549 response of bird functional types to climate and land-use change; Buchmann et al. (2011) used
550 the methodology to predict the home range and the spatial body mass distribution of species in
551 terrestrial mammal communities in fragmented landscapes; And, for a theoretical study of eco-
552 evolutionary dynamics, Pontarp and Wiens (2017) simulated the evolutionary radiation of a clade
553 across several habitats with differing environmental conditions.

554

555 Predator-prey interactions were considered from a functional perspective relatively early on in

556 the history of trait-based approaches, i.e. when generalist and specialist functional types were
557 introduced into modelling (Hanski et al., 1991). Functional traits are a much more recent
558 characteristic of predator-prey modelling studies, e.g. in a general additive model of beetle
559 predation with eight predator traits and four prey traits (Brousseau et al., 2018). The novelty of
560 these models is that the combination of functional traits and phylogeny overcome the limitations
561 of purely descriptive approaches. Where predator-prey interactions are combined into a food web
562 model, body size is often the central trait. This was the case in an allometric trophic network
563 model that explicitly featured intra- and interspecific interference including predator-prey
564 interactions in beetles and spiders (Laubmeier et al., 2018). Pathogen-host interactions resemble
565 predator-prey interactions in many ways as demonstrated by the interactions of amphibian
566 species and their fungal pathogens. In this case, the interactions were modelled with a statistical
567 approach investigating the predictive power of traits related to phylogenetic history, habitat use,
568 and life history traits (Gervasi et al., 2017). Individual- and trait-based movement models are
569 very powerful when it comes to scaling-up across several levels of organization. This feature was
570 exploited in an individual-based model that scaled up from individual movement and behavior to
571 metacommunity structure (Hirt et al., 2018).

572

573 Species distributions and species niches were modelled for the cane toad with a statistical
574 approach (Kearney et al., 2008; Kolbe et al., 2010) and for endotherms (Porter and Kearney,
575 2009) and ants (Diamond et al., 2012) with an equation-based approach. For the endotherms and
576 the ants, biophysical principles were used to link variation in functional traits with environmental
577 data to predict thermal niches (Porter and Kearney, 2009; Diamond et al., 2012).

578

579 Community assembly and dynamics were studied with equation-based models which, for
580 example, accounted for spatial variation in community structure with a multi-region multi-species
581 occupancy model (Tenan et al., 2017), investigated irreversible changes in community structure
582 in a consumer-resource model (Haney and Siepielski, 2018); and used trait-mediated interactions
583 to analyze invasiveness and invasibility of ecological networks (Hui et al., 2016). The need to
584 include such process-based components in community assembly models was emphasized by
585 Pontarp and Petchey (2016).

586

587 The models in this section show a great diversity of applications for the trait-based modelling of
588 animals in terrestrial ecosystems. However, each topic is represented by one or very few studies.
589 This indicates that there is scope for more applications in these and related fields, regardless of
590 model type.

591

592 **3. Trait-based modelling of aquatic ecosystems**

593 According to Litchman and Klausmeier (2008), the trait-based approach was first used for
594 modelling aquatic ecosystems in a model of a phytoplankton community by Ramon Margalef
595 (Margalef, 1978). Nevertheless, Follows and Dutkiewicz (2011), in their analysis of the state of
596 the art of marine ecosystems, concluded that trait-based approaches were just then (i.e. in 2011)
597 starting to be used in marine ecosystem models. The conflict between these two statements
598 demonstrates different understandings of what a trait-based model is.

599

600 In addition to the research papers, we also found that reviews on trait-based approaches for
601 studying aquatic ecosystems are not uncommon. Therefore, we shortly summarize the most
602 important reviews here. Litchman et al. (2010) reviewed trait-based approaches applied to
603 phytoplankton and revealed a new trend – to look at a trait and the phylogenetic structure of
604 communities simultaneously. This trend, in combination with adaptive trait models, makes it
605 possible to predict trait evolution. In another review on trait-based approaches for studying
606 phytoplankton, Bonachela et al. (2016) showed that it is also possible to successfully use trait-
607 based models to identify and compare possible survival strategies described by a set of functional
608 traits. These models typically include trade-offs between traits such as cell-size and resource
609 allocation.

610

611 In the following sections, we first review aquatic trait-based models including those for fish and
612 then those focusing on plankton. There are few trait-based modelling studies of other aquatic
613 realms, which are briefly covered in this paragraph, e.g. studies of bivalve species distribution
614 models (Montalto et al., 2015), inland freshwater communities (Gardner et al., 2014), coral reefs
615 (Edmunds et al., 2014; Madin et al., 2014), a pelagic microbial mixotrophic food web (Castellani
616 et al., 2013), marine benthic communities (Alexandridis et al., 2017), diatoms in peatlands

617 (Hagerthey et al., 2012) or trace metal concentrations in invertebrates (Hug Peter et al., 2018).
618 Traits were usually the inputs for models but in one case were outputs (Rinaldi et al. 2014). In
619 that paper, mechanistic functional trait models were used to predict life history traits such as body
620 size and fecundity of shellfish in lagoons. The fact that traits were used both as inputs and outputs
621 for models emphasizes the difference between effect traits and response traits (Fig. 1), two
622 concepts introduced earlier to terrestrial ecological theory (Lavorel and Garnier, 2002).

623

624 *3.1. Trait-based models including fish*

625 Trait-based modelling is widely applied to modelling fish communities. Of those models, the
626 overwhelming majority were equation-based models (Supplementary Material. Tab. 1). There
627 were only four individual-based models (Brochier et al., 2013; Houle et al., 2013; O’Farrell et al.,
628 2015; Huebert et al., 2018), one statistical model (Howeth et al., 2016) and one statistical and
629 conceptual model (Bennett et al., 2016) that generalized the trilateral life history model by
630 Winemiller and Rose (1992). This prevalence of equation-based models may be due to the fact
631 that aquatic ecosystems are more homogeneous than terrestrial ecosystems and therefore lend
632 themselves more naturally to the continuous character of most equation-based models.

633

634 Size appears to be the main structuring trait in aquatic ecosystems because size influences the
635 most important organism processes, such as foraging, growth, and reproduction. For example,
636 fish fall into different trophic levels when young than when old. Because size usually correlates
637 with age, trophic level in fish is linked to body size. Size structure prevails up to the community
638 level in marine ecosystems. This fact prompted the formulation of the community size spectrum
639 (Guiet et al., 2016b). The regularity of the community size-spectrum is expressed in the
640 constancy of total ecosystem biomass within “logarithmically equal body size intervals” (Guiet et
641 al., 2016b). Thus, community size-spectrum models represent the ecosystem using two
642 parameters – the slope and the intercept of the community size-spectrum. This type of model
643 mechanistically addresses the role of species diversity via the introduction of the trait size
644 (Hartvig et al., 2011; Maury and Poggiale, 2013; Guiet et al., 2016a). In these models,
645 community dynamics emerge from individual interactions. Trait-based size-spectrum models
646 were developed with a range of goals, including to study the benefit to fish of the reproductive

647 strategy of producing many small eggs or to analyze coexistence between species and link it to
648 maturation sizes and predator-prey size ratios (Hartvig and Andersen, 2013). Trait-based size-
649 spectrum models also demonstrate the impact of fishing on species composition (Shephard et al.,
650 2012), i.e. that fishing out larger individuals shifts the size spectrum towards the dominance of
651 smaller species.

652

653 Originally, Andersen and Beyer (2006) introduced a size- and trait-based model to estimate
654 fishing effects at the ecosystem level. In this model, every individual was characterized by two
655 features: body size and asymptotic body size. This model was later expanded (Houle et al., 2013;
656 Zhang et al., 2013; Jacobsen et al., 2014; Jennings and Collingridge, 2015). The asymptotic body
657 size was defined as a main trait because it is the basis for applying life history theory to estimate
658 size at maturity and reproductive output (Jennings and Collingridge, 2015). The indirect
659 influence of fishing on community structure was revealed by an extended version of the initial
660 model considering entire life histories and individual energy budgets (Kolding et al., 2016).

661 Another size- and trait-based model included individual interactions in the form of competition
662 and predation and individual processes such as encounters, growth, mortality and reproduction
663 (Jacobsen et al., 2014). A similar model was developed by Andersen and Pedersen (2010) and
664 Andersen and Rice (2010). In this model, all basic processes at the community level emerged
665 directly or indirectly from individual-level processes. To answer the question how to maximize
666 fishing yield under a certain conservation constraint, Andersen et al. (2015) suggested a
667 conceptual size- and trait-based model. An adaptation and a dynamic version of the model of a
668 theoretical ‘fish community’ (Pope et al., 2006), based on classical multi-species fishery models
669 and community size spectrum models, was reconsidered by Andersen and Pedersen (2010) and
670 Andersen et al. (2015) in the framework of a trait-based approach. A similar model to describe
671 population structure based on the size of the organisms was presented by Hartvig et al. (2011)
672 and Hartvig and Andersen (2013). This model was a product of the synthesis between traditional
673 unstructured food webs, allometric body size scaling, trait-based modelling, and physiologically
674 structured modelling (Hartvig et al., 2011). These approaches were further developed into more
675 complex food web models that showed that climate change effects are highly unpredictable
676 (Zhang et al., 2014; Zhang et al., 2017). Using Approximate Bayesian Computation in their food
677 web model, Melián et al. 2014 highlighted the importance of accounting for intraspecific

678 variability when investigating species coexistence. Such combinations of traditional approaches
679 with novel modelling techniques provides a promising new approach to the study of size-
680 structured food webs.

681

682 Other examples, which we briefly describe in this section, covered the topics of marine
683 biodiversity exploitation, marine community modelling including seal species (Houle et al.,
684 2016), adaptive behavioral responses, fish-mesozooplankton interactions, fish-jellyfish
685 interactions and freshwater fish modelling. Marine biodiversity exploitation was studied with an
686 object-oriented individual-based model (Brochier et al., 2013). This model incorporated four
687 main categories of life history depending on which part of the life cycle fish spent in the estuary
688 studied. To reduce the computing power needed, Brochier et al. (2013) used a super-individual
689 approach (Scheffer et al., 1995) with one individual representing a fish school. They also created
690 15 groups of ecologically similar model species, each representing a group of real species
691 (Ecoutin et al., 2010). Each group contained one or more super-individuals with similar trophic
692 position and ecological traits. Persistent spatial interactions and cascading behavioral interactions
693 were revealed in a marine ecosystem model with detailed size structure and life cycles of
694 mesozooplankton and fish (Castellani et al., 2013). This model became a step towards a
695 mechanistic and adaptive representation of the upper trophic levels in ecosystem models. In this
696 model the main trait was size at maturation. Based on a traditional ocean ecosystem model
697 including chemistry, phytoplankton, micro- and mesozooplankton (Schrum et al., 2006), a new
698 model version replaced the compound group of mesozooplankton by a developmental stage- and
699 species-specific matrix and introduced fish feeding on mesozooplankton (Castellani et al., 2013).
700 A general mechanistic food web model of fish-jellyfish competitive interactions was based on the
701 feeding traits of fish and jellyfish populations (Schnedler-Meyer et al., 2016). The model also
702 incorporated, in addition to feeding traits, elemental composition, allometric scaling of vital rates,
703 locomotion, and life-history traits. The model predicted fish dominance at low primary
704 production and a shift towards jellyfish with increasing productivity, turbidity and fishing.

705

706 A few freshwater studies included one on the simulation and screening of freshwater fish
707 invasion which were tackled with the help of trait-based statistical models that used classification
708 trees (Howeth et al. 2016). Another example investigated temperature-dependent colonization

709 and extinction rates of darter fish in a body size-centered dynamic occupancy model (Shea et al.,
710 2015). Stochastic integral projection models were not only used for plants and terrestrial animals,
711 but also in a trait-based modelling study of pike in a freshwater ecosystem (Vindenes et al.,
712 2014).

713

714 On the basis of these publications, we believe there is no question that the long and successful
715 history of trait-based modelling including fish centered on size spectrums will continue. Future
716 applications are likely to further improve model predictions by following the increasing number
717 of examples where traits other than size are also included in the models.

718

719 *3.2. Trait-based models focusing on plankton*

720 As with fish, it is also possible to explicitly model plankton in a trait-based way (Follows et al.,
721 2007; Litchman et al., 2007; Bruggeman and Kooijman, 2007; Kiørboe, 2011). The models used
722 are predominantly equation-based models, as they were for those including fish discussed in the
723 previous section (Supplementary Material. Tab. 1). Similarly, the models considered size as the
724 main functional trait. Only two models were supplemented with individual-based modules (Clark
725 et al., 2013; Pastor et al., 2018), two adopted a statistical approach (Litchman et al., 2007;
726 Terseleer et al., 2014), and one a conceptual approach (Glibert, 2016). The great majority of these
727 models targeted the ecosystem level. This focus on ecosystems is possibly also one of the reasons
728 for the domination of equation-based approaches because such approaches are particularly well
729 suited to capture ecosystem fluxes.

730

731 The marine ecosystem model by Follows et al. (2007) became a starting point for the
732 development of a number of trait-based models in microbial ecology and plankton research. This
733 is probably because it successfully reproduced the observed global distributions and community
734 structure of the phytoplankton. The model included a diverse phytoplankton community that was
735 described by a set of physiological traits defined by field and laboratory data with related trade-
736 offs.

737

738 Phytoplankton cell size, and especially the drivers of small cell size, were addressed with a trait-

739 based model of cellular resource allocation (Clark et al., 2013). This model considered a three-
740 way trade-off between cell size, nutrient and light affinity, and growth rate. It was developed as a
741 combination of a classic nutrient-phytoplankton-zooplankton model and ‘cost-benefit’ models.
742 The trait-based approach was supported by individual-based modelling such that individual life
743 histories gave rise to the evolutionary dynamics of the whole system. This bottom-up approach
744 allowed missing ecosystem processes to be derived from model data. Where many individuals are
745 similar, as in the general case of plankton and the specific case of this model (Clark et al., 2013),
746 super-individuals can be created that represent groups of individuals with similar traits. As in
747 other super-individual applications (e.g. Brochier et al., 2013 in section 3.1. Trait-based models
748 including fish), this approach reduces computing power requirements. Plankton cell size and the
749 mechanisms underlying observed biogeographical difference in cell size were also studied by
750 Acevedo-Trejos et al. (2015) and Acevedo-Trejos et al. (2018). Their models considered trade-
751 offs between cell size and nutrient uptake, zooplankton grazing, and phytoplankton sinking.
752 Macroscopic system properties such as total biomass, mean trait values, and trait variance were
753 studied with a continuous trait-based phytoplankton model (Chen and Smith, 2018). This model
754 was developed as a sub-module of a larger model the goal of which was to simulate ocean
755 dynamics. The model produced realistic patterns of phytoplankton mean size and size diversity.
756 Co-evolution of traits with respect to chromatic and temperature adaptation was studied with a
757 trait-based ecosystem model (Hickman et al., 2010). Trait-based models with adaptive traits were
758 compared to trait-group resolving models in a study of phytoplankton communities in partially
759 mixed water columns (Peeters and Straile, 2018).

760

761 Disease transmission in multi-host communities was the focus of a multi-generational plankton-
762 based model that considered epidemiological traits such as foraging or exposure rate, conversion
763 efficiency, susceptibility, virulence and spore yield (Strauss et al., 2015). This model succeeded
764 in improving the mechanistic and predictive clarity of the dilution effect by connecting a
765 reduction in diluter species with the increase in disease risk. The dilution effect probably explains
766 links between host communities and transmission. In their model of virus infection of plankton
767 based on life-history traits, Beckett and Weitz (2018) found that lysis rates were driven by the
768 strains with the fastest replication and not those with the greatest abundance.

769

770 Compared to models with better resolved species-specific representations of physiological
771 processes, improved representation of biodiversity was suggested in a biodiversity-based marine
772 ecosystem model (Bruggeman and Kooijman, 2007). The model was based on a system of
773 infinite diversity in which species were defined by continuous trait values for light-harvesting
774 investment and nutrient-harvesting investment. The traits chosen affected all parts of the
775 metabolism forming a trade-off between harvesting and net growth. Based on this model and a
776 model by Bruggeman (2009), a trait-based model was developed to include mixotrophy,
777 succession and evolution of unicellular planktonic organisms and to predict optimum trophic
778 strategies of species under changing environmental conditions (Berge et al., 2017). This model
779 contained three key resource-harvesting traits: photosynthesis, phagotrophy and inorganic
780 nutrient uptake. To distinguish two different mixotrophic strategies, Chakraborty et al. (2017)
781 extended the model by Berge et al. (2017) by explicitly incorporating cell size and introducing a
782 pure heterotrophic strategy.

783

784 Different aspects of plankton ecosystems were recently scrutinized at greater detail, including
785 trait-based ecosystem function predictions for a global lake data set (Zwart et al., 2015),
786 biological interactions, species extinctions, nutrient uptake kinetics, and some theoretical
787 properties as well as more applied implications of plankton models. Interactions were
788 investigated in the form of temperature dependence of competition of phytoplankton species
789 (Bestion et al., 2018) and of host-pathogen interactions between zooplankton and a fungal
790 pathogen, which seem to be mediated by host foraging under climate warming (Shocket et al.,
791 2018). Species extinctions strengthen the relationship between biodiversity and resource use
792 efficiency (Smeti et al., 2018) based on a model studying phytoplankton succession (Roelke and
793 Spatharis, 2015a) and assemblage characteristics (Roelke and Spatharis, 2015b). Based on
794 insights from a size-based model on nutrient uptake kinetics of phytoplankton, Smith et al. (2014)
795 emphasized that plankton ecology benefits from mechanistic trait-based models that account for
796 physiological trade-offs. In a theoretical exercise, Gaedke and Klauschies (2017) showed that the
797 knowledge of the shape of observed trait distributions is beneficial for the elegant analysis of
798 aggregate plankton models, because it allows for data-based moment closure. With a new scale-
799 invariant size-spectrum plankton model, Cuesta et al. (2018) explored the constancy of the
800 relationship between biomass density and logarithmic body mass across scales. Finally, there

801 were examples of trait-based plankton models that explicitly addressed applied questions such as
802 the management of harmful algal blooms (Glibert, 2016; Follett et al., 2018).

803

804 The vibrant field of trait-based plankton models is a good example of how trait-based approaches
805 can inspire ecosystem modelling. The relatively homogeneous conditions in aquatic
806 environments lead to the dominance of one trait – size – over any other trait or any taxonomic
807 category in explanations of community and ecosystem processes and patterns. Thus, trait-based
808 approaches are more suitable than species-based approaches to model aquatic communities and
809 ecosystems.

810

811 **4. Trait-based models on microorganisms and soil decomposers**

812 Microorganisms and soil decomposers are relatively new subjects of trait-based modelling and
813 are still often represented as functional groups or functional types rather than traits. Therefore,
814 the following seven examples also included classifications into functional groups. As in models
815 of aquatic ecosystems, the models of microorganisms and soil decomposers were built around the
816 key trait body size and were predominantly equation-based (Supplementary Material. Tab. 1)
817 with the exception of one statistical model (Van Bellen et al., 2017). In terms of scale, all but one
818 model in this section operated at the community level. This one exception targeted continental to
819 global scales (Wieder et al., 2015). Such scales are surprisingly large for a model including
820 microbial processes.

821

822 Nitrification by ammonia-oxidizing bacteria, ammonia-oxidizing archaea and nitrite-oxidizing
823 bacteria was considered in a mechanistic trait-based model (Bouskill et al., 2012). It was based
824 on traits connected to the enzyme kinetics of nitrite. Another version of this model simulated the
825 influence of global change on ecological niches of soil nitrite-oxidizing bacteria types (Le Roux
826 et al., 2016). This trait-based model grouped nitrite-oxidizing bacteria into a few functional
827 groups. The authors demonstrate that this approach was successful because three main bacteria
828 functional types expressed contrasting responses to environmental changes.

829

830 Using functional types can be inferior to using functional traits. This was demonstrated by
831 another microbial model that addressed time lags in the enzymatic response of denitrifying

832 microorganisms to changes in substrate concentration, including the interactive dynamics
833 between enzymes and nutrients (Song et al., 2017). This model linked community traits with
834 functional enzymes, not species or functional guilds as in previous studies (Taffs et al., 2009;
835 Bouskill et al., 2012). With organisms whose multiple functions overlapped with one another, the
836 guild-based (functional type) approach failed to properly represent these organisms. Enzyme- and
837 thus trait-based implementations therefore provide tools for scaling up biogeochemical functions
838 to the community level without involving the dynamics of individual species or their guilds.

839

840 A physiological trade-off between the traits of drought tolerance and carbon use efficiency was at
841 the core of two modelling studies on soil decomposition (Allison, 2012; Allison and Goulден,
842 2017). In these models, the decomposition submodel of enzymatic traits was derived from the
843 phytoplankton model by Follows et al. (2007) to predict litter decomposition rates in soil. The
844 sensitivity of microbial traits, community dynamics, and litter decomposition to variation in
845 drought tolerance costs was quantified in an updated model (Allison and Goulден, 2017). The
846 model implied that, for the Mediterranean climate system, seasonal drought was a more important
847 environmental filter than reduced precipitation during the wet season. These models were
848 examples of successful exchange between disciplines.

849

850 There were few general trait-based models that are applicable to terrestrial and marine
851 ecosystems alike. One of the rare cases, Harfoot et al. (2014), was a general ecosystem model
852 based on eight traits thought to be the most important for determining rates of ecological
853 processes. These traits were realm, nutrition source, mobility, leaf strategy, feeding mode,
854 reproductive strategy, thermoregulation mode, and body mass. This model benefited from a
855 coupled individual- and equation-based approach. The equation-based approach was applied to
856 autotrophs and the individual-based one to all other organisms. In this way, ecosystem structure
857 and function emerged from interactions at the individual level. However, the individuals in this
858 model were in fact groups or cohorts of organisms (the super-individual approach, Scheffer et al.,
859 1995). This model showed that highly complex models require the combination of different
860 modelling approaches including simplification tools such as the super-individual approach.

861

862 All in all, the variety of models in all sections demonstrates that trait-based modelling approaches

863 are useful tools that are able to facilitate modelling and improve the predictive power of model
864 outcomes across taxa and disciplines. In this variety of models, we nevertheless see a number of
865 trends. One of these is a shift from functional types to functional traits. There is also a search for
866 generalizations across organisms with similar functions and a few examples that scale-up
867 processes from the local to the global level. Techniques that appear to be useful, especially in
868 individual-based models, are the super-individual approach and the incorporation of intraspecific
869 trait-variability. Nevertheless, it seems clear from both empirical and modelling studies that the
870 development of trait-based models did not produce a universal set of traits. Therefore, researchers
871 should instead select traits according to the research question and strategies of the organisms
872 under investigation.

873

874 **Discussion and Conclusions**

875 Based on our systematic review, it is clear that trait-based approaches are as valuable in
876 modelling studies as they were earlier in empirical studies. They facilitate parameterization and
877 scaling-up of models as well as the generalization of their results. Despite some inconsistencies
878 in the terminology of trait-based studies, trait-based models have been implemented widely for
879 different groups of organisms and ecosystems, in different model types, and for achieving a broad
880 range of aims (See Supplement Material. Table 1). We observed productive exchange of trait-
881 based modelling concepts and techniques, especially between vegetation ecology and other
882 disciplines, and argue that this should be intensified and extended to more disciplines in the
883 future.

884

885 Inconsistencies in terminology within trait-based approaches mainly originate from the unclear
886 differentiation between functional types and functional traits as categories for grouping
887 organisms. For example, Jeltsch et al. (2008) suggested three strategies for applying plant
888 functional type approaches in modelling, where the “functional trait” strategy was one of them -
889 together with “functional group” and “functional species” strategies. Jeltsch et al. (2008) also
890 pointed to the fact that it was not possible to easily separate these strategies from each other. In
891 any case, none of the modelling papers explicitly use the classification by Jeltsch et al. (2008). If
892 researchers did so, it would certainly clarify terminology.

893

894 In our review, we distinguish between models applying functional types and functional traits,
895 following the shift in the theoretical literature from describing vegetation types to describing
896 vegetation function (Moore and Noble, 1990; Webb et al., 2010) reflected in the development of
897 DGVMs (Van Bodegom et al., 2012). The inconsistent use of terminology biases systematic
898 reviews that use key words in search engines. For example, some papers state that they
899 implement a novel trait-based modelling approach although in practice they use functional types.
900 Other papers clearly consider well-developed trait-based models but are not found using that key
901 word (e.g. Seifan et al., 2012). Some studies develop crucial theoretical frameworks or methods
902 that are probably useful for future model development and validation but do not themselves use
903 any model. They advocate, for example, incorporating arbuscular mycorrhizal fungi in trait-based
904 models (Treseder, 2016), including community trait distributions to overcome the challenge of
905 estimating single traits (Edwards, 2016), considering intraspecific variability (Burton et al.,
906 2017), or using remotely sensed data to parameterize trait-based models (McDowell and Xu,
907 2017). Nevertheless, not all facets of trait-based modelling seem to be sufficiently well known in
908 all fields of ecology to warrant correct attribution of a study to this method. Thus, unambiguous
909 terminology requires more attention in the future. Adhering to a consistent terminology will also
910 simplify the exchange of trait-based concepts between different disciplines.

911

912 Exchange of ideas on implementing trait-based models occurred between the fields of vegetation
913 ecology, marine ecology, limnology, animal ecology and microbial ecology. This exchange
914 already started with the first trait-based approaches from plant functional ecology (Lavorel &
915 Garnier, 2002; Wright et al., 2004) being adopted by animal studies of bats (Lentini et al., 2015)
916 and birds (Scherer et al., 2016). In ecological modelling, ideas were transferred from
917 phytoplankton research (Follows et al., 2007) to a litter decomposition model (Allison, 2012).
918 We encourage the expansion of such exchange of trait-based modelling approaches between
919 disciplines. These exchanges are likely to be most promising for cases where different organisms
920 have similar functions in their communities.

921

922 Trait-based models have been implemented for answering a number of ecological research
923 questions from basic and applied ecology. Basic ecological questions that were addressed with
924 trait-based models included goals such as identifying which mechanisms drive plant growth, how

925 populations develop over time and space, how communities assemble and biodiversity can be
926 explained, as well as which factors influence community dynamics. Applied trait-based
927 modelling studies investigated biological invasion conditions and consequences, responses of
928 ecosystems to climate and land-use change, conservation and management planning, as well as
929 the evaluation of ecosystem services. We see potential for the reinforcement of trait-based
930 modelling approaches in areas such as the assessment of ecosystem services, invasion prediction
931 and prevention, biodiversity studies, connection to demographic approaches (Salguero-Gómez,
932 Violle, Gimenez, & Childs, 2018) and, especially, the prediction of community and ecosystem
933 responses under climate and land-use changes.

934

935 Many model types were employed to implement trait-based approaches. The greatest proportion
936 was equation-based models. The next greatest proportion was that of statistical models that
937 describe patterns and demonstrate correlations between, for example, functional traits and
938 environmental filters. The combination of trait-based approaches with process-based modelling,
939 as one subcategory of equation-based modelling, is particularly interesting because the detailed
940 representation of physiological processes in process-based models may not at first be compatible
941 with the aggregated approach of trait-based models. However, once united in a model, it is
942 possibly just these different perspectives on a study system that, by complementing each other,
943 will overcome the limitations from which the constituent approaches suffer when used in
944 isolation (Scheiter and Higgins, 2009; Ali et al., 2015; Holzwarth et al., 2015). Combined
945 process- and trait-based models are also able to capture a broader range of scales than each
946 approach alone. Trait-based models are challenging to implement at extreme scales because the
947 trait concept aggregates information too much for very fine-scale models and too little for very
948 broad-scale models. However, traits are successfully integrated into process-based models that
949 implement plant physiology at fine scales and into DGVMs and earth system models at global
950 scales. Furthermore, we see a specific advantage to implementing trait-based approaches in
951 individual-based models (May et al., 2009; Scheiter et al., 2013; Weiss et al., 2014; Pontarp and
952 Wiens, 2017). It is possible to link traits directly to environment conditions and they are therefore
953 considered to be an adequate tool for investigating community responses to environmental
954 gradients (McGill et al., 2006; Webb et al., 2010). Combined with individual-based models
955 (Grimm and Railsback, 2005; DeAngelis and Mooij, 2005), trait-based approaches have several

956 advantages: They are able to offer sufficient flexibility to simplify the description of individuals,
957 to capture plant-plant interactions at the individual level and thereby explain local community-
958 level phenomena (Jeltsch et al., 2008), and to facilitate model parameterization based on trait data
959 that are becoming increasingly available through databases (Weiss et al., 2014; Grimm and
960 Berger, 2016). Trait databases will become an even richer source for trait-based modelling once
961 they expand their current focus on plants to other organisms and start collecting and offering
962 information on abiotic and biotic interactions as well as intraspecific trait variation (Funk et al.,
963 2016).

964

965 We conclude that although trait-based modelling approaches have rapidly increased in ecology
966 over the past twenty years, the potential advantages of the method have not yet been fully
967 exploited. Key terms should be uniquely defined and the main concepts of the theoretical
968 framework should be unambiguously clarified. We recommend developing and applying trait-
969 based models to study community structure and dynamics and to attempt predicting the direction
970 and intensity of community changes under global climate and land-use change. The complexity
971 of such community-level studies is outweighed by the usually lower parameterization effort and
972 more general model outcomes of trait-based modelling approaches. We recommend combining
973 individual-based with trait-based approaches more frequently to benefit from the enhanced
974 flexibility. Moreover, trait-based modelling enables the capturing of the feedback from
975 communities to the environment, as long as the model includes the effects as well as the
976 responses of ecosystems and traits. Trait-based modelling is therefore able to become an
977 important contributor to a comprehensive understanding of community structure and dynamics
978 under global change.

979

980 Abrego, N., Norberg, A., Ovaskainen, O., 2017. Measuring and predicting the influence of traits on the
981 assembly processes of wood-inhabiting fungi. *J. Ecol.* 105, 1070–1081.

982 <https://doi.org/10.1111/1365-2745.12722>

983 Acevedo-Trejos, E., Brandt, G., Bruggeman, J., Merico, A., 2015. Mechanisms shaping size structure and
984 functional diversity of phytoplankton communities in the ocean. *Sci. Rep.* 5, 17–20.

985 <https://doi.org/10.1038/srep08918>

986 Acevedo-Trejos, E., Marañón, E., Merico, A., 2018. Phytoplankton size diversity and ecosystem function

- 987 relationships across oceanic regions. *Proc. R. Soc. B Biol. Sci.* 285.
988 <https://doi.org/10.1098/rspb.2018.0621>
- 989 Adler, P.B., Salguero-Gomez, R., Compagnoni, A., Hsu, J.S., Ray-Mukherjee, J., Mbeau-Ache, C.,
990 Franco, M., 2014. Functional traits explain variation in plant life history strategies. *Proc. Natl. Acad.*
991 *Sci.* 111, 740–745. <https://doi.org/10.1073/pnas.1315179111>
- 992 Albert, C.H., Grassein, F., Schurr, F.M., Vieilledent, G., Violle, C., 2011. When and how should
993 intraspecific variability be considered in trait-based plant ecology? *Perspect. Plant Ecol. Evol. Syst.*
994 13, 217–225. <https://doi.org/10.1016/J.PPEES.2011.04.003>
- 995 Alexandridis, N., Dambacher, J.M., Jean, F., Desroy, N., Bacher, C., 2017. Qualitative modelling of
996 functional relationships in marine benthic communities. *Ecol. Modell.* 360, 300–312.
997 <https://doi.org/10.1016/j.ecolmodel.2017.07.021>
- 998 Ali, A.A., Medlyn, B.E., Aubier, T.G., Crous, K.Y., Reich, P.B., 2015. Elevated carbon dioxide is
999 predicted to promote coexistence among competing species in a trait-based model. *Ecol. Evol.* 5,
1000 4717–4733. <https://doi.org/10.1002/ece3.1733>
- 1001 Ali, A.A., Medlyn, B.E., Crous, K.Y., Reich, P.B., 2013. A trait-based ecosystem model suggests that
1002 long-term responsiveness to rising atmospheric CO₂ concentration is greater in slow-growing than
1003 fast-growing plants. *Funct. Ecol.* 27, 1011–1022. <https://doi.org/10.1111/1365-2435.12102>
- 1004 Allison, S.D., 2012. A trait-based approach for modelling microbial litter decomposition. *Ecol. Lett.* 15,
1005 1058–1070. <https://doi.org/10.1111/j.1461-0248.2012.01807.x>
- 1006 Allison, S.D., Goulden, M.L., 2017. Consequences of drought tolerance traits for microbial decomposition
1007 in the DEMENT model. *Soil Biol. Biochem.* 107, 104–113.
1008 <https://doi.org/10.1016/j.soilbio.2017.01.001>
- 1009 Andersen, K.H., Beyer, J.E., 2006. Asymptotic Size Determines Species Abundance in the Marine Size
1010 Spectrum. *Am. Nat.* 168, 54–61. <https://doi.org/10.1086/504849>
- 1011 Andersen, K.H., Brander, K., Ravn-Jensen, L., 2015. Trade-offs between objectives for ecosystem
1012 management of fisheries. *Ecol. Appl.* 25, 1390–1396. <https://doi.org/10.1890/14-1209.1>
- 1013 Andersen, K.H., Pedersen, M., 2010. Damped trophic cascades driven by fishing in model marine
1014 ecosystems. *Proc. R. Soc. B Biol. Sci.* 277, 795–802. <https://doi.org/10.1098/rspb.2009.1512>
- 1015 Andersen, K.H., Rice, J.C., 2010. Direct and indirect community effects of rebuilding plans. *ICES J. Mar.*

- 1016 Sci. 67, 1980–1988. <https://doi.org/10.1093/icesjms/fsq035>
- 1017 Astegiano, J., Guimarães, P.R., Cheptou, P.O., Vidal, M.M., Mandai, C.Y., Ashworth, L., Massol, F.,
1018 2015. Persistence of plants and pollinators in the face of habitat loss: Insights from trait-based
1019 metacommunity models, 1st ed, Advances in Ecological Research. Elsevier Ltd.
1020 <https://doi.org/10.1016/bs.aecr.2015.09.005>
- 1021 Aubry-Kientz, M., Rossi, V., Boreux, J.J., Hérault, B., 2015. A joint individual-based model coupling
1022 growth and mortality reveals that tree vigor is a key component of tropical forest dynamics. *Ecol.*
1023 *Evol.* 5, 2457–2465. <https://doi.org/10.1002/ece3.1532>
- 1024 Beckett, S.J., Weitz, J.S., 2018. The Effect of Strain Level Diversity on Robust Inference of Virus-
1025 Induced Mortality of Phytoplankton. *Front. Microbiol.* 9, 1–15.
1026 <https://doi.org/10.3389/fmicb.2018.01850>
- 1027 Bennett, M.G., Whiles, M.R., Whitley, G.W., 2016. Population-level responses of life history traits to
1028 flow regime in three common stream fish species. *Ecohydrology* 9, 1388–1399.
1029 <https://doi.org/10.1002/eco.1734>
- 1030 Berge, T., Chakraborty, S., Hansen, P.J., Andersen, K.H., 2017. Modeling succession of key resource-
1031 harvesting traits of mixotrophic plankton. *ISME J.* 11, 212–223.
1032 <https://doi.org/10.1038/ismej.2016.92>
- 1033 Bestion, E., García-Carreras, B., Schaum, C.E., Pawar, S., Yvon-Durocher, G., 2018. Metabolic traits
1034 predict the effects of warming on phytoplankton competition. *Ecol. Lett.* 21, 655–664.
1035 <https://doi.org/10.1111/ele.12932>
- 1036 Bhaskar, R., Dawson, T.E., Balvanera, P., 2014. Community assembly and functional diversity along
1037 succession post-management. *Funct. Ecol.* 28, 1256–1265. <https://doi.org/10.1111/1365-2435.12257>
- 1038 Bolnick, D.I., Amarasekare, P., Araújo, M.S., Bürger, R., Levine, J.M., Novak, M., Rudolf, V.H.W.,
1039 Schreiber, S.J., Urban, M.C., Vasseur, D.A., 2011. Why intraspecific trait variation matters in
1040 community ecology. *Trends Ecol. Evol.* 26, 183–192. <https://doi.org/10.1016/j.tree.2011.01.009>
- 1041 Bonachela, J.A., Klausmeier, C.A., Edwards, K.F., Litchman, E., Levin, S.A., 2016. The role of
1042 phytoplankton diversity in the emergent oceanic stoichiometry. *J. Plankton Res.* 38, 1021–1035.
1043 <https://doi.org/10.1093/plankt/fbv087>
- 1044 Bouskill, N.J., Tang, J., Riley, W.J., Brodie, E.L., 2012. Trait-based representation of biological
1045 nitrification: Model development, testing, and predicted community composition. *Front. Microbiol.*

- 1046 3, 1–17. <https://doi.org/10.3389/fmicb.2012.00364>
- 1047 Bown, J.L., Pachepsky, E., Eberst, A., Bausenwein, U., Millard, P., Squire, G.R., Crawford, J.W., 2007.
1048 Consequences of intraspecific variation for the structure and function of ecological communities.
1049 Part 1. Model development and predicted patterns of diversity. *Ecol. Modell.* 207, 264–276.
1050 <https://doi.org/10.1016/j.ecolmodel.2007.05.004>
- 1051 Brochier, T., Ecoutin, J.M., de Morais, L.T., Kaplan, D.M., Lae, R., 2013. A multi-agent ecosystem model
1052 for studying changes in a tropical estuarine fish assemblage within a marine protected area. *Aquat.*
1053 *Living Resour.* 26, 147–158. <https://doi.org/10.1051/alr/2012028>
- 1054 Brousseau, P.-M., Gravel, D., Handa, I.T., 2018. On the development of a predictive functional trait
1055 approach for studying terrestrial arthropods. *J. Anim. Ecol.* 1209–1220.
1056 <https://doi.org/10.1111/1365-2656.12834>
- 1057 Bruggeman, J., 2009. Succession in plankton communities - A trait-based perspective. *Dep. Theor. Biol.*
- 1058 Bruggeman, J., Kooijman, S.A.L.M., 2007. A biodiversity-inspired approach to aquatic ecosystem
1059 modeling. *Limnol. Oceanogr.* 52, 1533–1544. <https://doi.org/10.4319/lo.2007.52.4.1533>
- 1060 Buchmann, C.M., Schurr, F.M., Nathan, R., Jeltsch, F., 2011. An allometric model of home range
1061 formation explains the structuring of animal communities exploiting heterogeneous resources. *Oikos*
1062 120, 106–118. <https://doi.org/10.1111/j.1600-0706.2010.18556.x>
- 1063 Burton, J.I., Perakis, S.S., McKenzie, S.C., Lawrence, C.E., Puettmann, K.J., 2017. Intraspecific
1064 variability and reaction norms of forest understorey plant species traits. *Funct. Ecol.* 31, 1881–1893.
1065 <https://doi.org/10.1111/1365-2435.12898>
- 1066 Castellani, M., Rosland, R., Urtizberea, A., Fiksen, Ø., 2013. A mass-balanced pelagic ecosystem model
1067 with size-structured behaviourally adaptive zooplankton and fish. *Ecol. Modell.* 251, 54–63.
1068 <https://doi.org/10.1016/j.ecolmodel.2012.12.007>
- 1069 Chakraborty, S., Nielsen, L.T., Andersen, K.H., 2017. Trophic Strategies of Unicellular Plankton. *Am.*
1070 *Nat.* 189, E77–E90. <https://doi.org/10.1086/690764>
- 1071 Chapin, F.S., Zavaleta, E.S., Eviner, V.T., Naylor, R.L., Vitousek, P.M., Reynolds, H.L., Hooper, D.U.,
1072 Lavorel, S., Sala, O.E., Hobbie, S.E., Mack, M.C., Díaz, S., 2000. Consequences of changing
1073 biodiversity. *Nature* 405, 234–242. <https://doi.org/10.1038/35012241>
- 1074 Chauvet, M., Kunstler, G., Roy, J., Morin, X., 2017. Using a forest dynamics model to link community

- 1075 assembly processes and traits structure. *Funct. Ecol.* 31, 1452–1461. <https://doi.org/10.1111/1365->
1076 2435.12847
- 1077 Chavana-Bryant, C., Malhi, Y., Wu, J., Asner, G.P., Anastasiou, A., Enquist, B.J., Cosio Caravasi, E.G.,
1078 Doughty, C.E., Saleska, S.R., Martin, R.E., Gerard, F.F., 2017. Leaf aging of Amazonian canopy
1079 trees as revealed by spectral and physiochemical measurements. *New Phytol.* 214, 1049–1063.
1080 <https://doi.org/10.1111/nph.13853>
- 1081 Chave, J., Andalo, C., Brown, S., Cairns, M.A., Chambers, J.Q., Eamus, D., Fölster, H., Fromard, F.,
1082 Higuchi, N., Kira, T., Lescure, J.P., Nelson, B.W., Ogawa, H., Puig, H., Riéra, B., Yamakura, T.,
1083 2005. Tree allometry and improved estimation of carbon stocks and balance in tropical forests.
1084 *Oecologia* 145, 87–99. <https://doi.org/10.1007/s00442-005-0100-x>
- 1085 Chave, J., Coomes, D., Jansen, S., Lewis, S.L., Swenson, N.G., Zanne, A.E., 2009. Towards a worldwide
1086 wood economics spectrum. *Ecol. Lett.* 12, 351–366. <https://doi.org/10.1111/j.1461->
1087 0248.2009.01285.x
- 1088 Chen, B., Smith, S.L., 2018. CITRATE 1.0: Phytoplankton continuous trait-distribution model with one-
1089 dimensional physical transport applied to the Northwest Pacific. *Geosci. Model Dev.* 11, 467–495.
1090 <https://doi.org/10.5194/gmd-11-467-2018>
- 1091 Clark, D.L., Wilson, M., Roberts, R., Dunwiddie, P.W., Stanley, A., Kaye, T.N., 2012. Plant traits - a tool
1092 for restoration? *Appl. Veg. Sci.* 15, 449–458. <https://doi.org/10.1111/j.1654-109X.2012.01198.x>
- 1093 Clark, J.R., Lenton, T.M., Williams, H.T.P., Daines, S.J., 2013. Environmental selection and resource
1094 allocation determine spatial patterns in picophytoplankton cell size. *Limnol. Oceanogr.* 58, 1008–
1095 1022. <https://doi.org/10.4319/lo.2013.58.3.1008>
- 1096 Colbach, N., Granger, S., Guyot, S.H.M., Mézière, D., 2014. A trait-based approach to explain weed
1097 species response to agricultural practices in a simulation study with a cropping system model. *Agric.*
1098 *Ecosyst. Environ.* 183, 197–204. <https://doi.org/10.1016/j.agee.2013.11.013>
- 1099 Cox, D.R., Hinkley, D.V., Hinkley, D.V., 1979. *Theoretical Statistics*. Chapman and Hall/CRC.
1100 <https://doi.org/10.1201/b14832>
- 1101 Crowther, T.W., Maynard, D.S., Crowther, T.R., Peccia, J., Smith, J.R., Bradford, M.A., 2014. Untangling
1102 the fungal niche: The trait-based approach. *Front. Microbiol.* 5, 1–12.
1103 <https://doi.org/10.3389/fmicb.2014.00579>
- 1104 Cuddington, K., Fortin, M.-J., Gerber, L.R., Hastings, A., Liebhold, A., O'Connor, M., Ray, C., 2013.

- 1105 Process-based models are required to manage ecological systems in a changing world. *Ecosphere* 4,
1106 art20. <https://doi.org/10.1890/ES12-00178.1>
- 1107 Cuesta, J.A., Delius, G.W., Law, R., 2018. Sheldon spectrum and the plankton paradox: two sides of the
1108 same coin—a trait-based plankton size-spectrum model. *J. Math. Biol.* 76, 67–96.
1109 <https://doi.org/10.1007/s00285-017-1132-7>
- 1110 DeAngelis, D.L., Grimm, V., 2014. Individual-based models in ecology after four decades. *F1000Prime*
1111 Rep. 6, 39. <https://doi.org/10.12703/P6-39>
- 1112 DeAngelis, D.L., Mooij, W.M., 2005. Individual-Based Modeling of Ecological and Evolutionary
1113 Processes. *Annu. Rev. Ecol. Evol. Syst.* 36, 147–168.
1114 <https://doi.org/10.1146/annurev.ecolsys.36.102003.152644>
- 1115 Diamond, S.E., Nichols, L.M., McCoy, N., Hirsch, C., Pelini, S.L., Sanders, N.J., Ellison, A.M., Gotelli,
1116 N.J., Dunn, R.R., 2012. A physiological trait-based approach to predicting the responses of species
1117 to experimental climate warming. *Ecology* 93, 2305–2312. <https://doi.org/10.1890/11-2296.1>
- 1118 Diaz, S., Cabido, M., 1997. Plant functional types and ecosystem function in relation to global change. *J.*
1119 *Veg. Sci.* 8, 463–474. <https://doi.org/10.2307/3237198>
- 1120 Díaz, S., Kattge, J., Cornelissen, J.H.C., Wright, I.J., Lavorel, S., Dray, S., Reu, B., Kleyer, M., Wirth, C.,
1121 Prentice, I.C., Garnier, E., Bönsch, G., Westoby, M., Poorter, H., Reich, P.B., Moles, A.T., Dickie,
1122 J., Gillison, A.N., Zanne, A.E., Chave, J., Wright, S.J., Sheremet'ev, S.N., Jactel, H., Christopher,
1123 B., Cerabolini, B., Pierce, S., Shipley, B., Kirkup, D., Casanoves, F., Joswig, J.S., Günther, A.,
1124 Falczuk, V., Rüger, N., Mahecha, M.D., Gorné, L.D., 2015. The global spectrum of plant form and
1125 function. *Nature* 529, 1–17. <https://doi.org/10.1038/nature16489>
- 1126 Diaz, S., Lavorel, S., de Bello, F., Quetier, F., Grigulis, K., Robson, T.M., 2007. Incorporating plant
1127 functional diversity effects in ecosystem service assessments. *Proc. Natl. Acad. Sci.* 104, 20684–
1128 20689. <https://doi.org/10.1073/pnas.0704716104>
- 1129 Drewniak, B., Gonzalez-Meler, M.A., 2017. Earth system model needs for including the interactive
1130 representation of nitrogen deposition and drought effects on forested ecosystems. *Forests* 8, 1–22.
1131 <https://doi.org/10.3390/f8080267>
- 1132 Ecoutin, J.M., Simier, M., Albaret, J.J., Laë, R., Tito de Morais, L., 2010. Changes over a decade in fish
1133 assemblages exposed to both environmental and fishing constraints in the Sine Saloum estuary
1134 (Senegal). *Estuar. Coast. Shelf Sci.* 87, 284–292. <https://doi.org/10.1016/J.ECSS.2010.01.009>

- 1135 Edmunds, P.J., Adjeroud, M., Baskett, M.L., Baums, I.B., Budd, A.F., Carpenter, R.C., Fabina, N.S., Fan,
1136 T.Y., Franklin, E.C., Gross, K., Han, X., Jacobson, L., Klaus, J.S., McClanahan, T.R., O'Leary, J.K.,
1137 Van Oppen, M.J.H., Pochon, X., Putnam, H.M., Smith, T.B., Stat, M., Sweatman, H., Van Woesik,
1138 R., Gates, R.D., 2014. Persistence and change in community composition of reef corals through
1139 present, past, and future climates. *PLoS One* 9. <https://doi.org/10.1371/journal.pone.0107525>
- 1140 Edwards, K.F., 2016. Community trait structure in phytoplankton: Seasonal dynamics from a method for
1141 sparse trait data. *Ecology* 97, 3441–3451. <https://doi.org/10.1002/ecy.1581>
- 1142 Enquist, B.J., Kerkhoff, A.J., Stark, S.C., Swenson, N.G., McCarthy, M.C., Price, C. a, 2007. A general
1143 integrative model for scaling plant growth, carbon flux, and functional trait spectra. *Nature* 449,
1144 218–222. <https://doi.org/10.1038/nature06061>
- 1145 Eviner, V.T., Chapin III, F.S., 2003. Functional Matrix: A Conceptual Framework for Predicting Multiple
1146 Plant Effects on Ecosystem Processes. *Annu. Rev. Ecol. Evol. Syst.* 34, 455–485.
1147 <https://doi.org/10.1146/annurev.ecolsys.34.011802.132342>
- 1148 Falster, D.S., Brännström, Å., Dieckmann, U., Westoby, M., 2011. Influence of four major plant traits on
1149 average height, leaf-area cover, net primary productivity, and biomass density in single-species
1150 forests: A theoretical investigation. *J. Ecol.* 99, 148–164. <https://doi.org/10.1111/j.1365-2745.2010.01735.x>
- 1152 Follett, C.L., Dutkiewicz, S., Karl, D.M., Inomura, K., Follows, M.J., 2018. Seasonal resource conditions
1153 favor a summertime increase in North Pacific diatom-diazotroph associations. *ISME J.* 12, 1543–
1154 1557. <https://doi.org/10.1038/s41396-017-0012-x>
- 1155 Follows, M.J., Dutkiewicz, S., 2011. Modeling Diverse Communities of Marine Microbes. *Ann. Rev.*
1156 *Mar. Sci.* 3, 427–451. <https://doi.org/10.1146/annurev-marine-120709-142848>
- 1157 Follows, M.J., Dutkiewicz, S., Grant, S., Chisholm, S.W., 2007. Emergent biogeography of microbial
1158 communities in a model ocean. *Science* (80-.). 315, 1843–1846.
1159 <https://doi.org/10.1126/science.1138544>
- 1160 Fort, F., Volaire, F., Guillioni, L., Barkaoui, K., Navas, M.L., Roumet, C., 2017. Root traits are related to
1161 plant water-use among rangeland Mediterranean species. *Funct. Ecol.* 31, 1700–1709.
1162 <https://doi.org/10.1111/1365-2435.12888>
- 1163 Frenette-Dussault, C., Shipley, B., Meziane, D., Hingrat, Y., 2013. Trait-based climate change predictions
1164 of plant community structure in arid steppes. *J. Ecol.* 101, 484–492. <https://doi.org/10.1111/1365->

- 1165 2745.12040
- 1166 Funk, J.L., Larson, J.E., Ames, G.M., Butterfield, B.J., Cavender-Bares, J., Finn, J., Laughlin, D.C.,
1167 Sutton-Grier, A.E., Williams, L., Wright, J., 2017. Revisiting the Holy Grail: using plant functional
1168 traits to understand ecological processes. *Biol. Rev.* 92, 1156–1173.
1169 <https://doi.org/10.1111/brv.12275>
- 1170 Funk, J.L., Standish, R.J., Stock, W.D., Valladares, F., 2016. Plant functional traits of dominant native and
1171 invasive species in mediterranean-climate ecosystems. *Ecology* 97, 75–83.
1172 <https://doi.org/10.1890/15-0974.1>
- 1173 Fyllas, N.M., Gloor, E., Mercado, L.M., Sitch, S., Quesada, C.A., Domingues, T.F., Galbraith, D.R.,
1174 Torre-Lezama, A., Vilanova, E., Ramírez-Angulo, H., Higuchi, N., Neill, D.A., Silveira, M.,
1175 Ferreira, L., Aymard C., G.A., Malhi, Y., Phillips, O.L., Lloyd, J., 2014. Analysing Amazonian
1176 forest productivity using a new individual and trait-based model (TFS v.1). *Geosci. Model Dev.* 7,
1177 1251–1269. <https://doi.org/10.5194/gmd-7-1251-2014>
- 1178 Gaedke, U., Klauschies, T., 2017. Analyzing the shape of observed trait distributions enables a data-based
1179 moment closure of aggregate models. *Limnol. Oceanogr. Methods* 15, 979–994.
1180 <https://doi.org/10.1002/lom3.10218>
- 1181 Gardner, R.H., Engelhardt, K.A.M., Elmore, A.J., Cadol, D., 2014. A traits-based model of species
1182 diversity. *Ecol. Modell.* 288, 178–194. <https://doi.org/10.1016/j.ecolmodel.2014.06.006>
- 1183 Garnier, E., Navas, M.L., 2012. A trait-based approach to comparative functional plant ecology: Concepts,
1184 methods and applications for agroecology. A review, *Agronomy for Sustainable Development*.
1185 <https://doi.org/10.1007/s13593-011-0036-y>
- 1186 Garnier, E., Shipley, B., 2001. A standardized protocol for the determination of specific leaf area and leaf
1187 dry matter content. *Funct. Ecol.* 15, 688–695. <https://doi.org/10.1046/j.0269-8463.2001.00563.x>
- 1188 Garrard, G.E., McCarthy, M.A., Williams, N.S.G., Bekessy, S.A., Wintle, B.A., 2013. A general model of
1189 detectability using species traits. *Methods Ecol. Evol.* 4, 45–52. <https://doi.org/10.1111/j.2041-210x.2012.00257.x>
- 1191 Gervasi, S.S., Stephens, P.R., Hua, J., Searle, C.L., Xie, G.Y., Urbina, J., Olson, D.H., Bancroft, B.A.,
1192 Weis, V., Hammond, J.I., Relyea, R.A., Blaustein, A.R., 2017. Linking ecology and epidemiology to
1193 understand predictors of multi-host responses to an emerging pathogen, the amphibian chytrid
1194 fungus. *PLoS One* 12, 1–23. <https://doi.org/10.1371/journal.pone.0167882>

- 1195 Glibert, P.M., 2016. Margalef revisited: A new phytoplankton mandala incorporating twelve dimensions,
1196 including nutritional physiology. *Harmful Algae* 55, 25–30.
1197 <https://doi.org/10.1016/j.hal.2016.01.008>
- 1198 Grigulis, K., Lavorel, S., Krainer, U., Legay, N., Baxendale, C., Dumont, M., Kastl, E., Arnoldi, C.,
1199 Bardgett, R.D., Poly, F., Pommier, T., Schloter, M., Tappeiner, U., Bahn, M., Clément, J.-C., 2013.
1200 Relative contributions of plant traits and soil microbial properties to mountain grassland ecosystem
1201 services. *J. Ecol.* 101, 47–57. <https://doi.org/10.1111/1365-2745.12014>
- 1202 Grime, J.P., 1974. Vegetation classification by reference to strategies. *Nature* 250, 26–31.
1203 <https://doi.org/10.1038/250026a0>
- 1204 Grimm, V., Berger, U., 2016. Structural realism, emergence, and predictions in next-generation ecological
1205 modelling: Synthesis from a special issue. *Ecol. Modell.* 326, 177–187.
1206 <https://doi.org/10.1016/j.ecolmodel.2016.01.001>
- 1207 Grimm, V., Railsback, S.F., 2005. Individual-based modeling and ecology. Princeton series in theoretical
1208 and computational biology.
- 1209 Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S.F., Thulke, H.-H., Weiner, J.,
1210 Wiegand, T., DeAngelis, D.L., 2005. Pattern-Oriented Modeling of Agent Based Complex Systems:
1211 Lessons from Ecology. *Am. Assoc. Adv. Sci.* 310, 987–991.
1212 <https://doi.org/10.1126/science.1116681>
- 1213 Guet, J., Aumont, O., Poggiale, J.C., Maury, O., 2016a. Effects of lower trophic level biomass and water
1214 temperature on fish communities: A modelling study. *Prog. Oceanogr.* 146, 22–37.
1215 <https://doi.org/10.1016/j.pocean.2016.04.003>
- 1216 Guet, J., Poggiale, J.C., Maury, O., 2016b. Modelling the community size-spectrum: recent developments
1217 and new directions. *Ecol. Modell.* 337, 4–14. <https://doi.org/10.1016/j.ecolmodel.2016.05.015>
- 1218 Hagerthey, S.E., Newman, S., Xue, S., 2012. Periphyton-based transfer functions to assess ecological
1219 imbalance and management of a subtropical ombrotrophic peatland. *Freshw. Biol.* 57, 1947–1965.
1220 <https://doi.org/10.1111/j.1365-2427.2012.02848.x>
- 1221 Haney, S.D., Siepielski, A.M., 2018. Tipping Points in Resource Abundance Drive Irreversible Changes
1222 in Community Structure. *Am. Nat.* 191, 000–000. <https://doi.org/10.1086/697045>
- 1223 Hanski, I., Hansson, L., Henttonen, H., 1991. Specialist Predators, Generalist Predators, and the Microtine
1224 Rodent Cycle. *J. Anim. Ecol.* 60, 353. <https://doi.org/10.2307/5465>

- 1225 Harfoot, M.B.J., Newbold, T., Tittensor, D.P., Emmott, S., Hutton, J., Lyutsarev, V., Smith, M.J.,
1226 Scharlemann, J.P.W., Purves, D.W., 2014. Emergent Global Patterns of Ecosystem Structure and
1227 Function from a Mechanistic General Ecosystem Model. *PLoS Biol.* 12.
1228 <https://doi.org/10.1371/journal.pbio.1001841>
- 1229 Harper, A.B., Cox, P.M., Friedlingstein, P., Wiltshire, A.J., Jones, C.D., Sitch, S., Mercado, L.M.,
1230 Groenendijk, M., Robertson, E., Kattge, J., Bönisch, G., Atkin, O.K., Bahn, M., Cornelissen, J.,
1231 Niinemets, Ü., Onipchenko, V., Peñuelas, J., Poorter, L., Reich, P.B., Soudzilovskaia, N.A., Van
1232 Bodegom, P., 2016. Improved representation of plant functional types and physiology in the Joint
1233 UK Land Environment Simulator (JULES v4.2) using plant trait information. *Geosci. Model Dev.* 9,
1234 2415–2440. <https://doi.org/10.5194/gmd-9-2415-2016>
- 1235 Harte, J., Shaw, R., 1995. Shifting Dominance Within a Montane Vegetation Community: Results of a
1236 Climate-Warming Experiment. *Science* (80-.). 267, 876–880.
1237 <https://doi.org/10.1126/science.267.5199.876>
- 1238 Hartvig, M., Andersen, K.H., 2013. Coexistence of structured populations with size-based prey selection.
1239 *Theor. Popul. Biol.* 89, 24–33. <https://doi.org/10.1016/j.tpb.2013.07.003>
- 1240 Hartvig, M., Andersen, K.H., Beyer, J.E., 2011. Food web framework for size-structured populations. *J.*
1241 *Theor. Biol.* 272, 113–122. <https://doi.org/10.1016/j.jtbi.2010.12.006>
- 1242 Hérault, B., Bachelot, B., Poorter, L., Rossi, V., Bongers, F., Chave, J., Paine, C.E.T., Wagner, F.,
1243 Baraloto, C., 2011. Functional traits shape ontogenetic growth trajectories of rain forest tree species.
1244 *J. Ecol.* 99, 1431–1440. <https://doi.org/10.1111/j.1365-2745.2011.01883.x>
- 1245 Herron, P.M., Martine, C.T., Latimer, A.M., Leicht-Young, S.A., 2007. Invasive plants and their
1246 ecological strategies: Prediction and explanation of woody plant invasion in New England. *Divers.*
1247 *Distrib.* 13, 633–644. <https://doi.org/10.1111/j.1472-4642.2007.00381.x>
- 1248 Hickman, A.E., Dutkiewicz, S., Williams, R.G., Follows, M.J., 2010. Modelling the effects of chromatic
1249 adaptation on phytoplankton community structure in the oligotrophic ocean. *Mar. Ecol. Prog. Ser.*
1250 406, 1–17. <https://doi.org/10.3354/meps08588>
- 1251 Higgins, S.I., Richardson, D.M., 1998. Pine invasions in the southern hemisphere: modeling interactions
1252 between organism, environment and disturbance. *Plant Ecol.* 135, 79–93.
1253 <https://doi.org/10.1023/a:1009760512895>
- 1254 Hirt, M.R., Grimm, V., Li, Y., Rall, B.C., Rosenbaum, B., Brose, U., 2018. Bridging Scales: Allometric

- 1255 Random Walks Link Movement and Biodiversity Research. *Trends Ecol. Evol.* 33, 701–712.
1256 <https://doi.org/10.1016/j.tree.2018.07.003>
- 1257 Hodgson, J.G., Wilson, P.J., Hunt, R., Grime, J.P., Thompson, K., 1999. Allocating C-S-R Plant
1258 Functional Types: A Soft Approach to a Hard Problem. *Oikos* 85, 282.
1259 <https://doi.org/10.2307/3546494>
- 1260 Hof, A.R., Rodríguez-Castañeda, G., Allen, A.M., Jansson, R., Nilsson, C., 2017. Vulnerability of
1261 Subarctic and Arctic breeding birds: *Ecol. Appl.* 27, 219–234. <https://doi.org/10.1002/eap.1434>
- 1262 Holzwarth, F., Rüger, N., Wirth, C., 2015. Taking a closer look: disentangling effects of functional
1263 diversity on ecosystem functions with a trait-based model across hierarchy and time. *R. Soc. open*
1264 *Sci.* 2, 140541. <https://doi.org/10.1098/rsos.140541>
- 1265 Homolova, L., Schaeppman, M.E., Lamarque, P., Clevers, J.G.P.W., De Bello, F., Thuiller, W., Lavorel, S.,
1266 2014. Comparison of remote sensing and plant trait-based modelling to predict ecosystem services in
1267 subalpine grasslands. *Ecosphere* 5, 1–29. <https://doi.org/10.1890/ES13-00393.1>
- 1268 Houle, J.E., Andersen, K.H., Farnsworth, K.D., Reid, D.G., 2013. Emerging asymmetric interactions
1269 between forage and predator fisheries impose management trade-offsa. *J. Fish Biol.* 83, 890–904.
1270 <https://doi.org/10.1111/jfb.12163>
- 1271 Houle, J.E., de Castro, F., Cronin, M.A., Farnsworth, K.D., Gosch, M., Reid, D.G., 2016. Effects of seal
1272 predation on a modelled marine fish community and consequences for a commercial fishery. *J. Appl.*
1273 *Ecol.* 53, 54–63. <https://doi.org/10.1111/1365-2664.12548>
- 1274 Howeth, J.G., Gantz, C.A., Angermeier, P.L., Frimpong, E.A., Hoff, M.H., Keller, R.P., Mandrak, N.E.,
1275 Marchetti, M.P., Olden, J.D., Romagosa, C.M., Lodge, D.M., 2016. Predicting invasiveness of
1276 species in trade: climate match, trophic guild and fecundity influence establishment and impact of
1277 non-native freshwater fishes. *Divers. Distrib.* 22, 148–160. <https://doi.org/10.1111/ddi.12391>
- 1278 Huebert, K.B., Pätsch, J., Hufnagl, M., Kreuz, M., Peck, M.A., 2018. Modeled larval fish prey fields and
1279 growth rates help predict recruitment success of cod and anchovy in the North Sea. *Mar. Ecol. Prog.*
1280 *Ser.* 600, 111–126. <https://doi.org/10.3354/meps12615>
- 1281 Hug Peter, D., Sardy, S., Diaz Rodriguez, J., Castella, E., Slaveykova, V.I., 2018. Modeling whole body
1282 trace metal concentrations in aquatic invertebrate communities: A trait-based approach. *Environ.*
1283 *Pollut.* 233, 419–428. <https://doi.org/10.1016/j.envpol.2017.10.044>
- 1284 Hui, C., Richardson, D.M., Landi, P., Minoarivelo, H.O., Garnas, J., Roy, H.E., 2016. Defining

- 1285 invasiveness and invasibility in ecological networks. *Biol. Invasions* 18, 971–983.
1286 <https://doi.org/10.1007/s10530-016-1076-7>
- 1287 Jabot, F., 2010. A stochastic dispersal-limited trait-based model of community dynamics. *J. Theor. Biol.*
1288 262, 650–661. <https://doi.org/10.1016/j.jtbi.2009.11.004>
- 1289 Jack, C.N., Friesen, M.L., Hintze, A., Sheneman, L., 2017. Third-party mutualists have contrasting effects
1290 on host invasion under the enemy-release and biotic-resistance hypotheses. *Evol. Ecol.* 31, 829–845.
1291 <https://doi.org/10.1007/s10682-017-9912-5>
- 1292 Jacobsen, N.S., Gislason, H., Andersen, K.H., 2014. The consequences of balanced harvesting of fish
1293 communities. *Proc. R. Soc. B Biol. Sci.* 281, 20132701–20132701.
1294 <https://doi.org/10.1098/rspb.2013.2701>
- 1295 Jaffré, M., Le Galliard, J.F., 2016. Population viability analysis of plant and animal populations with
1296 stochastic integral projection models. *Oecologia* 182, 1031–1043. [https://doi.org/10.1007/s00442-](https://doi.org/10.1007/s00442-016-3704-4)
1297 [016-3704-4](https://doi.org/10.1007/s00442-016-3704-4)
- 1298 Jeltsch, F., Moloney, K.A., Schurr, F.M., Köchy, M., Schwager, M., 2008. The state of plant population
1299 modelling in light of environmental change. *Perspect. Plant Ecol. Evol. Syst.* 9, 171–189.
1300 <https://doi.org/10.1016/j.ppees.2007.11.004>
- 1301 Jennings, S., Collingridge, K., 2015. Predicting consumer biomass, size-structure, production, catch
1302 potential, responses to fishing and associated uncertainties in the world’s marine ecosystems. *PLoS*
1303 *One* 10, 1–28. <https://doi.org/10.1371/journal.pone.0133794>
- 1304 Kattge, J., Diaz, S., Lavorel, S., Prentice, I.C., Leadley, P., Boenisch, G., Garnier, E., Westoby, M., Reich,
1305 P.B., Wright, I.J., Cornelissen, J.H.C., Violle, C., Harrison, S.P., Van Bodegom, P.M., Reichstein,
1306 M., Enquist, B.J., Soudzilovskaia, N.A., Ackerly, D.D., Anand, M., Atkin, O., Bahn, M., Baker,
1307 T.R., Baldocchi, D., Bekker, R., Blanco, C.C., Blonder, B., Bond, W.J., Bradstock, R., Bunker, D.E.,
1308 Casanoves, F., Cavender-Bares, J., Chambers, J.Q., Chapin III, F.S., Chave, J., Coomes, D.,
1309 Cornwell, W.K., Craine, J.M., Dobrin, B.H., Duarte, L., Durka, W., Elser, J., Esser, G., Estiarte, M.,
1310 Fagan, W.F., Fang, J., Fernandez-Mendez, F., Fidelis, A., Finegan, B., Flores, O., Ford, H., Frank,
1311 D., Freschet, G.T., Fyllas, N.M., Gallagher, R. V., Green, W.A., Gutierrez, A.G., Hickler, T.,
1312 Higgins, S.I., Hodgson, J.G., Jalili, A., Jansen, S., Joly, C.A., Kerkhoff, A.J., Kirkup, D., Kitajima,
1313 K., Kleyer, M., Klotz, S., Knops, J.M.H., Kramer, K., Kühn, I., Kurokawa, H., Laughlin, D., Lee,
1314 T.D., Leishman, M., Lens, F., Lenz, T., Lewis, S.L., Lloyd, J., Llusia, J., Louault, F., Ma, S.,
1315 Mahecha, M.D., Manning, P., Massad, T., Medlyn, B.E., Messier, J., Moles, A.T., Müller, S.C.,

- 1316 Nadrowski, K., Naeem, S., Niinemets, Ü., Nöllert, S., Nüske, A., Ogaya, R., Oleksyn, J.,
1317 Onipchenko, V.G., Onoda, Y., Ordonez, J., Overbeck, G., Ozinga, W.A., Patino, S., Paula, S.,
1318 Pausas, J.G., Penuelas, J., Phillips, O.L., Pillar, V., Poorter, H., Poorter, L., Poschlod, P., Prinzing,
1319 A., Proulx, R., Rammig, A., Reinsch, S., Reu, B., Sack, L., Salgado-Negret, B., Sardans, J.,
1320 Shiodera, S., Shipley, B., Siefert, A., Sosinski, E., Soussana, J.-F., Swaine, E., Swenson, N.,
1321 Thompson, K., Thornton, P., Waldram, M., Weiher, E., White, M., White, S., Wright, S.J., Yguel,
1322 B., Zaehle, S., Zanne, A.E., Wirth, C., 2011. TRY - a global database of plant traits. *Glob. Chang.*
1323 *Biol.* 17, 2905–2935. <https://doi.org/10.1111/j.1365-2486.2011.02451.x>
- 1324 Ke, P., Miki, T., Ding, T., 2015. Supporting Information The soil microbial community predicts the
1325 importance of plant traits in plant-soil feedback *Po-Ju* 329–341.
- 1326 Kearney, M., Phillips, B.L., Tracy, C.R., Christian, K.A., Betts, G., Porter, W.P., 2008. Modelling species
1327 distributions without using species distributions: the cane toad in Australia under current and future
1328 climates. *Ecography (Cop.)*. 31, 423–434. <https://doi.org/10.1111/j.2008.0906-7590-05457.x>
- 1329 Kiørboe, T., 2011. How zooplankton feed: Mechanisms, traits and trade-offs. *Biol. Rev.* 86, 311–339.
1330 <https://doi.org/10.1111/j.1469-185X.2010.00148.x>
- 1331 Kleyer, M., Bekker, R.M., Knevel, I.C., Bakker, J.P., Thompson, K., Sonnenschein, M., Poschlod, P., van
1332 Groenendael, J.M., Klimeš, L., Klimešová, J., Klotz, S., Rusch, G.M., Hermy, M., Adriaens, D.,
1333 Boedeltje, G., Bossuyt, B., Dannemann, A., Endels, P., Götzenberger, L., Hodgson, J.G., Jackel, A.-
1334 K., Kühn, I., Kunzmann, D., Ozinga, W.A., Römermann, C., Stadler, M., Schlegelmilch, J.,
1335 Steendam, H.J., Tackenberg, O., Wilmann, B., Cornelissen, J.H.C., Eriksson, O., Garnier, E., Peco,
1336 B., 2008. The LEDA Traitbase: a database of life-history traits of the Northwest European flora. *J.*
1337 *Ecol.* 96, 1266–1274. <https://doi.org/10.1111/j.1365-2745.2008.01430.x>
- 1338 Knapp, A.K., 2002. Rainfall Variability, Carbon Cycling, and Plant Species Diversity in a Mesic
1339 Grassland. *Science (80-.)*. 298, 2202–2205. <https://doi.org/10.1126/science.1076347>
- 1340 Kolbe, J.J., Kearney, M., Shine, R., 2010. Modeling the consequences of thermal trait variation for the
1341 cane toad invasion of Australia. *Ecol. Appl.* 20, 2273–2285. <https://doi.org/10.1890/09-1973.1>
- 1342 Kolding, J., Jacobsen, N.S., Andersen, K.H., van Zwieten, P.A.M., 2016. Maximizing fisheries yields
1343 while maintaining community structure. *Can. J. Fish. Aquat. Sci.* 73, 644–655.
1344 <https://doi.org/10.1139/cjfas-2015-0098>
- 1345 Kraft, N.J.B., Godoy, O., Levine, J.M., 2015. Plant functional traits and the multidimensional nature of
1346 species coexistence. *Proc. Natl. Acad. Sci.* 112, 797–802. <https://doi.org/10.1073/pnas.1413650112>

- 1347 Küster, E.C., Kühn, I., Bruelheide, H., Klotz, S., 2008. Trait interactions help explain plant invasion
1348 success in the German flora. *J. Ecol.* 96, 860–868. <https://doi.org/10.1111/j.1365-2745.2008.01406.x>
- 1349 Laliberté, E., Shipley, B., Norton, D.A., Scott, D., 2012. Which plant traits determine abundance under
1350 long-term shifts in soil resource availability and grazing intensity? *J. Ecol.* 100, 662–677.
1351 <https://doi.org/10.1111/j.1365-2745.2011.01947.x>
- 1352 Lamarque, P., Lavorel, S., Mouchet, M., Quétier, F., 2014. Plant trait-based models identify direct and
1353 indirect effects of climate change on bundles of grassland ecosystem services. *Proc. Natl. Acad. Sci.*
1354 *U. S. A.* 111, 13751–6. <https://doi.org/10.1073/pnas.1216051111>
- 1355 Larson, J.E., Funk, J.L., 2016. Regeneration: an overlooked aspect of trait-based plant community
1356 assembly models. *J. Ecol.* 104, 1284–1298. <https://doi.org/10.1111/1365-2745.12613>
- 1357 Laubmeier, A.N., Wootton, K., Banks, J.E., Bommarco, R., Curtsdotter, A., Jonsson, T., Roslin, T.,
1358 Banks, H.T., 2018. From theory to experimental design—Quantifying a trait-based theory of
1359 predator-prey dynamics. *PLoS One* 13, e0195919. <https://doi.org/10.1371/journal.pone.0195919>
- 1360 Laughlin, D.C., 2014. Applying trait-based models to achieve functional targets for theory-driven
1361 ecological restoration. *Ecol. Lett.* 17, 771–784. <https://doi.org/10.1111/ele.12288>
- 1362 Laughlin, D.C., 2011. Nitrification is linked to dominant leaf traits rather than functional diversity. *J. Ecol.*
1363 99, 1091–1099. <https://doi.org/10.1111/j.1365-2745.2011.01856.x>
- 1364 Laughlin, D.C., Fulé, P.Z., Huffman, D.W., Crouse, J., Laliberté, E., 2011. Climatic constraints on trait-
1365 based forest assembly. *J. Ecol.* 99, 1489–1499. <https://doi.org/10.1111/j.1365-2745.2011.01885.x>
- 1366 Laughlin, D.C., Joshi, C., 2015. Theoretical consequences of trait-based environmental filtering for the
1367 breadth and shape of the niche: New testable hypotheses generated by the TraitSpace model. *Ecol.*
1368 *Modell.* 307, 10–21. <https://doi.org/10.1016/j.ecolmodel.2015.03.013>
- 1369 Laughlin, D.C., Joshi, C., Richardson, S.J., Peltzer, D.A., Mason, N.W.H., Wardle, D.A., 2015.
1370 Quantifying multimodal trait distributions improves trait-based predictions of species abundances
1371 and functional diversity. *J. Veg. Sci.* 26, 46–57. <https://doi.org/10.1111/jvs.12219>
- 1372 Laughlin, D.C., Joshi, C., van Bodegom, P.M., Bastow, Z.A., Fulé, P.Z., 2012. A predictive model of
1373 community assembly that incorporates intraspecific trait variation. *Ecol. Lett.* 15, 1291–1299.
1374 <https://doi.org/10.1111/j.1461-0248.2012.01852.x>
- 1375 Laughlin, D.C., Laughlin, D.E., 2013. Advances in modeling trait-based plant community assembly.

- 1376 Trends Plant Sci. 18, 584–593. <https://doi.org/10.1016/j.tplants.2013.04.012>
- 1377 Laughlin, D.C., Strahan, R.T., Huffman, D.W., Sánchez Meador, A.J., 2017. Using trait-based ecology to
1378 restore resilient ecosystems: historical conditions and the future of montane forests in western North
1379 America. *Restor. Ecol.* 25, S135–S146. <https://doi.org/10.1111/rec.12342>
- 1380 Lavorel, S., Díaz, S., Cornelissen, J.H.C., Garnier, E., Harrison, S.P., McIntyre, S., Pausas, J.G., Pérez-
1381 Harguindeguy, N., Roumet, C., Urcelay, C., 2007. Plant functional types: are we getting any closer
1382 to the Holy Grail? *Terr. Ecosyst. a Chang. world* 149–160. https://doi.org/10.1300/J035v16n03_03
- 1383 Lavorel, S., Garnier, E., 2002. Predicting changes in community composition and ecosystem functioning
1384 from plant traits: revisiting the Holy Grail. *Funct. Ecol.* 16, 545–556. <https://doi.org/10.1046/j.1365->
1385 2435.2002.00664.x
- 1386 Lavorel, S., Garnier, E., 2002. Predicting changes in community composition and ecosystem functioning
1387 from plant traits: revisiting the Holy Grail. *Funct. Ecol.* 16, 545–556. <https://doi.org/10.1046/j.1365->
1388 2435.2002.00664.x
- 1389 Lavorel, S., Grigulis, K., Lamarque, P., Colace, M.P., Garden, D., Girel, J., Pellet, G., Douzet, R., 2011.
1390 Using plant functional traits to understand the landscape distribution of multiple ecosystem services.
1391 *J. Ecol.* 99, 135–147. <https://doi.org/10.1111/j.1365-2745.2010.01753.x>
- 1392 Lavorel, S., McIntyre, S., Landsberg, J., Forbes, T.D.A., 1997. Plant functional classifications: From
1393 general groups to specific groups based on response to disturbance. *Trends Ecol. Evol.*
1394 [https://doi.org/10.1016/S0169-5347\(97\)01219-6](https://doi.org/10.1016/S0169-5347(97)01219-6)
- 1395 Lavorel, S., Storkey, J., Bardgett, R.D., De Bello, F., Berg, M.P., Le Roux, X., Moretti, M., Mulder, C.,
1396 Pakeman, R.J., Díaz, S., Harrington, R., 2013. A novel framework for linking functional diversity of
1397 plants with other trophic levels for the quantification of ecosystem services. *J. Veg. Sci.* 24, 942–
1398 948. <https://doi.org/10.1111/jvs.12083>
- 1399 Le Roux, X., Bouskill, N.J., Niboyet, A., Barthes, L., Dijkstra, P., Field, C.B., Hungate, B.A., Lerondelle,
1400 C., Pommier, T., Tang, J., Terada, A., Tourna, M., Poly, F., 2016. Predicting the responses of soil
1401 nitrite-oxidizers to multi-factorial global change: A trait-based approach. *Front. Microbiol.* 7, 1–13.
1402 <https://doi.org/10.3389/fmicb.2016.00628>
- 1403 Lentini, P.E., Bird, T.J., Griffiths, S.R., Godinho, L.N., Wintle, B.A., 2015. A global synthesis of survival
1404 estimates for microbats. *Biol. Lett.* 11. <https://doi.org/10.1098/rsbl.2015.0371>
- 1405 Litchman, E., de Tezanos Pinto, P., Klausmeier, C.A., Thomas, M.K., Yoshiyama, K., 2010. Linking traits

- 1406 to species diversity and community structure in phytoplankton, in: Fifty Years after the “Homage to
1407 Santa Rosalia”: Old and New Paradigms on Biodiversity in Aquatic Ecosystems. Springer
1408 Netherlands, Dordrecht, pp. 15–28. https://doi.org/10.1007/978-90-481-9908-2_3
- 1409 Litchman, E., Klausmeier, C.A., 2008. Trait-Based Community Ecology of Phytoplankton. *Annu. Rev.*
1410 *Ecol. Evol. Syst.* 39, 615–639. <https://doi.org/10.1146/annurev.ecolsys.39.110707.173549>
- 1411 Litchman, E., Klausmeier, C.A., Schofield, O.M., Falkowski, P.G., 2007. The role of functional traits and
1412 trade-offs in structuring phytoplankton communities: Scaling from cellular to ecosystem level. *Ecol.*
1413 *Lett.* 10, 1170–1181. <https://doi.org/10.1111/j.1461-0248.2007.01117.x>
- 1414 Lochon, I., Colace, M.P., Devaux, C., Grigulis, K., Rettinger, R., Lavorel, S., 2018. Taxonomic and
1415 functional facets of the resilience to management of mown subalpine grasslands. *Appl. Veg. Sci.* 21,
1416 636–646. <https://doi.org/10.1111/avsc.12392>
- 1417 Losapio, G., Schöb, C., 2017. Resistance of plant-plant networks to biodiversity loss and secondary
1418 extinctions following simulated environmental changes. *Funct. Ecol.* 31, 1145–1152.
1419 <https://doi.org/10.1111/1365-2435.12839>
- 1420 Madin, J.S., Baird, A.H., Dornelas, M., Connolly, S.R., 2014. Mechanical vulnerability explains size-
1421 dependent mortality of reef corals. *Ecol. Lett.* 17, 1008–1015. <https://doi.org/10.1111/ele.12306>
- 1422 Margalef, R., 1978. Life-forms of phytoplankton as survival alternatives in an unstable environment.
1423 *Oceanol. Acta* 1, 493–509. <https://doi.org/10.1007/BF00202661>
- 1424 Marteinsdóttir, B., 2014. Seed rain and seed bank reveal that seed limitation strongly influences plant
1425 community assembly in grasslands. *PLoS One* 9. <https://doi.org/10.1371/journal.pone.0103352>
- 1426 Maury, O., Poggiale, J.-C.C., 2013. From individuals to populations to communities: A dynamic energy
1427 budget model of marine ecosystem size-spectrum including life history diversity. *J. Theor. Biol.* 324,
1428 52–71. <https://doi.org/10.1016/j.jtbi.2013.01.018>
- 1429 May, F., Grimm, V., Jeltsch, F., 2009. Reversed effects of grazing on plant diversity: The role of below-
1430 ground competition and size symmetry. *Oikos* 118, 1830–1843. <https://doi.org/10.1111/j.1600-0706.2009.17724.x>
- 1432 McDowell, N.G., Xu, C., 2017. Using traits to uncover tropical forest function. *New Phytol.* 214, 903–
1433 904. <https://doi.org/10.1111/nph.14576>
- 1434 McGill, B.J., Enquist, B.J., Weiher, E., Westoby, M., 2006. Rebuilding community ecology from

- 1435 functional traits. *Trends Ecol. Evol.* 21, 178–185. <https://doi.org/10.1016/j.tree.2006.02.002>
- 1436 McIntyre, S., Lavorel, S., Tremont, R.M., 1995. Plant Life-History Attributes: Their Relationship to
1437 Disturbance Response in Herbaceous Vegetation. *J. Ecol.* 83, 31. <https://doi.org/10.2307/2261148>
- 1438 Melián, C.J., Baldó, F., Matthews, B., Vilas, C., González-Ortegón, E., Drake, P., Williams, R.J., 2014.
1439 Chapter Six - Individual Trait Variation and Diversity in Food Webs, *Eco-Evolutionary Dynamics*.
1440 <https://doi.org/http://dx.doi.org/10.1016/B978-0-12-801374-8.00006-2>
- 1441 Merow, C., Latimer, A.M., Silander, J.A.J., 2011. Can entropy maximization use functional traits to
1442 explain species abundance? A comprehensive evaluation. *Ecology* 92, 1523–1537.
1443 <https://doi.org/10.1890/10-1174.1>
- 1444 Messier, J., McGill, B.J., Enquist, B.J., Lechowicz, M.J., 2017. Trait variation and integration across
1445 scales: is the leaf economic spectrum present at local scales? *Ecography (Cop.)*. 40, 685–697.
1446 <https://doi.org/10.1111/ecog.02006>
- 1447 Miki, T., Kondoh, M., 2002. Feedbacks between nutrient cycling and vegetation predict plant species
1448 coexistence and invasion. *Ecol. Lett.* 5, 624–633. <https://doi.org/10.1046/j.1461-0248.2002.00347.x>
- 1449 Montalto, V., Rinaldi, A., Sarà, G., 2015. Life history traits to predict biogeographic species distributions
1450 in bivalves. *Sci. Nat.* 102. <https://doi.org/10.1007/s00114-015-1313-4>
- 1451 Moor, H., 2017. Life history trade-off moderates model predictions of diversity loss from climate change.
1452 *PLoS One* 12, 1–21. <https://doi.org/10.1371/journal.pone.0177778>
- 1453 Moore, A.D., Noble, I.R., 1990. An individualistic model of vegetation stand dynamics. *J. Environ.*
1454 *Manage.* 31, 61–81. [https://doi.org/10.1016/S0301-4797\(05\)80015-5](https://doi.org/10.1016/S0301-4797(05)80015-5)
- 1455 Moran, E. V., Hartig, F., Bell, D.M., 2016. Intraspecific trait variation across scales: Implications for
1456 understanding global change responses. *Glob. Chang. Biol.* 22, 137–150.
1457 <https://doi.org/10.1111/gcb.13000>
- 1458 Mori, S., Yamaji, K., Ishida, A., Prokushkin, S.G., Masyagina, O. V., Hagihara, A., Hoque, A.T.M.R.,
1459 Suwa, R., Osawa, A., Nishizono, T., Ueda, T., Kinjo, M., Miyagi, T., Kajimoto, T., Koike, T.,
1460 Matsuura, Y., Toma, T., Zyryanova, O.A., Abaimov, A.P., Awaya, Y., Araki, M.G., Kawasaki, T.,
1461 Chiba, Y., Umari, M., 2010. Mixed-power scaling of whole-plant respiration from seedlings to giant
1462 trees. *Proc. Natl. Acad. Sci.* 107, 1447–1451. <https://doi.org/10.1073/pnas.0902554107>
- 1463 Mortensen, B., Abbott, K.C., Danielson, B., 2018. Defensive tradeoffs are not prerequisites to plant

- 1464 diversity in a two species model. *Oikos* 127, 63–72. <https://doi.org/10.1111/oik.04300>
- 1465 O’Farrell, S., Salguero-Gómez, R., van Rooij, J.M., Mumby, P.J., 2015. Disentangling trait-based
1466 mortality in species with decoupled size and age. *J. Anim. Ecol.* 84, 1446–1456.
1467 <https://doi.org/10.1111/1365-2656.12399>
- 1468 Otfinowski, R., Kenkel, N.C., Dixon, P., Wilmshurst, J.F., 2007. Integrating climate and trait models to
1469 predict the invasiveness of exotic plants in Canada’s Riding Mountain National Park. *Can. J. Plant*
1470 *Sci.* 87, 1001–1012. <https://doi.org/10.4141/CJPS07117>
- 1471 Ozgul, A., Bateman, A.W., English, S., Coulson, T., Clutton-Brock, T.H., 2014. Linking body mass and
1472 group dynamics in an obligate cooperative breeder. *J. Anim. Ecol.* 83, 1357–1366.
1473 <https://doi.org/10.1111/1365-2656.12239>
- 1474 Ozgul, A., Coulson, T., Reynolds, A., Cameron, T.C., Benton, T.G., 2012. Population Responses to
1475 Perturbations: The Importance of Trait-Based Analysis Illustrated through a Microcosm Experiment.
1476 *Am. Nat.* 179, 582–594. <https://doi.org/10.1086/664999>
- 1477 Pachepsky, E., Bown, J.L., Eberst, A., Bausenwein, U., Millard, P., Squire, G.R., Crawford, J.W., 2007.
1478 Consequences of intraspecific variation for the structure and function of ecological communities Part
1479 2: Linking diversity and function. *Ecol. Modell.* 207, 277–285.
1480 <https://doi.org/10.1016/j.ecolmodel.2007.05.005>
- 1481 Pachepsky, E., Crawford, J.W., Bown, J.L., Squire, G., 2001. Towards a general theory of biodiversity.
1482 *Nature* 410, 923–926. <https://doi.org/10.1038/35073563>
- 1483 Paleari, L., Movedi, E., Confalonieri, R., 2017. Trait-based model development to support breeding
1484 programs. A case study for salt tolerance and rice. *Sci. Rep.* 7, 1–11. <https://doi.org/10.1038/s41598-017-04022-y>
- 1486 Pastor, A., Mariani, P., Erichsen, A.C., Hansen, F.T., Hansen, J.L.S., 2018. Modeling dispersal and spatial
1487 connectivity of macro-invertebrates in Danish waters: An agent-based approach. *Reg. Stud. Mar.*
1488 *Sci.* 20, 45–59. <https://doi.org/10.1016/J.RSMA.2018.03.005>
- 1489 Pausas, J.G., 1999. Mediterranean vegetation dynamics: modelling problems and functional types. *Plant*
1490 *Ecol.* 140, 27–39. <https://doi.org/10.1023/A:1009752403216>
- 1491 Pavlick, R., Drewry, D.T., Bohn, K., Reu, B., Kleidon, A., 2012. The Jena Diversity-Dynamic Global
1492 Vegetation Model (JeDi-DGVM): a diverse approach to representing terrestrial biogeography and
1493 biogeochemistry based on plant functional trade-offs. *Biogeosciences Discuss.* 9, 4627–4726.

- 1494 <https://doi.org/10.5194/bgd-9-4627-2012>
- 1495 Peeters, F., Straile, D., 2018. Trait selection and co-existence of phytoplankton in partially mixed systems:
1496 Trait based modelling and potential of an aggregated approach. PLoS One 13, 1–21.
1497 <https://doi.org/10.1371/journal.pone.0194076>
- 1498 Pérez-Harguindeguy, N., Díaz, S., Garnier, E., Lavorel, S., Poorter, H., Jaureguiberry, P., Bret-Harte,
1499 M.S., Cornwell, W.K., Craine, J.M., Gurvich, D.E., Urcelay, C., Veneklaas, E.J., Reich, P.B.,
1500 Poorter, L., Wright, I.J., Ray, P., Enrico, L., Pausas, J.G., De Vos, A.C., Buchmann, N., Funes, G.,
1501 Quétier, F., Hodgson, J.G., Thompson, K., Morgan, H.D., Ter Steege, H., Van Der Heijden, M.G.A.,
1502 Sack, L., Blonder, B., Poschold, P., Vaieretti, M. V., Conti, G., Staver, A.C., Aquino, S.,
1503 Cornelissen, J.H.C., 2013. New handbook for standardised measurement of plant functional traits
1504 worldwide. Aust. J. Bot. 61, 167–234. <https://doi.org/10.1071/BT12225>
- 1505 Pontarp, M., Petchey, O.L., 2016. Community trait overdispersion due to trophic interactions: Concerns
1506 for assembly process inference. Proc. R. Soc. B Biol. Sci. 283.
1507 <https://doi.org/10.1098/rspb.2016.1729>
- 1508 Pontarp, M., Wiens, J.J., 2017. The origin of species richness patterns along environmental gradients:
1509 uniting explanations based on time, diversification rate and carrying capacity. J. Biogeogr. 44, 722–
1510 735. <https://doi.org/10.1111/jbi.12896>
- 1511 Pope, J.G., Rice, J.C., Daan, N., Jennings, S., Gislason, H., 2006. Modelling an exploited marine fish
1512 community with 15 parameters – results from a simple size-based model. ICES J. Mar. Sci. 63,
1513 1029–1044. <https://doi.org/10.1016/j.icesjms.2006.04.015>
- 1514 Porter, W.P., Kearney, M., 2009. Size, shape, and the thermal niche of endotherms. Proc. Natl. Acad. Sci.
1515 106, 19666–19672. <https://doi.org/10.1073/pnas.0907321106>
- 1516 Powney, G.D., Preston, C.D., Purvis, A., Van Landuyt, W., Roy, D.B., 2014. Can trait-based analyses of
1517 changes in species distribution be transferred to new geographic areas? Glob. Ecol. Biogeogr. 23,
1518 1009–1018. <https://doi.org/10.1111/geb.12189>
- 1519 Pöyry, J., Carvalheiro, L.G., Heikkinen, R.K., Kühn, I., Kuussaari, M., Schweiger, O., Valtonen, A., van
1520 Bodegom, P.M., Franzén, M., 2017. The effects of soil eutrophication propagate to higher trophic
1521 levels. Glob. Ecol. Biogeogr. 26, 18–30. <https://doi.org/10.1111/geb.12521>
- 1522 Prentice, I.C., Bondeau, A., Cramer, W., Harrison, S.P., Hickler, T., Lucht, W., Sitch, S., Smith, B.,
1523 Sykes, M.T., 2004. Dynamic Global Vegetation Modeling: Quantifying Terrestrial Ecosystem

- 1524 Responses to Large-Scale Environmental Change, in: *Terrestrial Ecosystems in a Changing World*.
1525 Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 175–192. [https://doi.org/10.1007/978-3-540-](https://doi.org/10.1007/978-3-540-32730-1_15)
1526 32730-1_15
- 1527 Quétier, F., Lavorel, S., Liancourt, P., Thébault, A., Davies, I.D., 2011. Assessing long-term land-use
1528 legacies in subalpine grasslands by using a plant trait-based generic modelling framework. *Plant*
1529 *Ecol. Divers.* 4, 391–402. <https://doi.org/10.1080/17550874.2011.629232>
- 1530 Quétier, F., Lavorel, S., Thuiller, W., Davies, I., 2007. Plant-trait-based modeling assessment of
1531 ecosystem-service sensitivity to land-use change. *Ecol. Appl.* 17, 2377–2386.
1532 <https://doi.org/10.1890/06-0750.1>
- 1533 Radny, J., Meyer, K.M., 2018. The role of biotic factors during plant establishment in novel communities
1534 assessed with an agent-based simulation model. *PeerJ* 6, e5342. <https://doi.org/10.7717/peerj.5342>
- 1535 Raunkiaer, C., 1934. *The Life Forms of Plants and Statistical Plant Geography*. *Life Forms Plants Stat.*
1536 *Plant Geogr.*
- 1537 Read, Q.D., Henning, J.A., Sanders, N.J., 2017. Intraspecific variation in traits reduces ability of trait-
1538 based models to predict community structure. *J. Veg. Sci.* 28, 1070–1081.
1539 <https://doi.org/10.1111/jvs.12555>
- 1540 Reich, P.B., Wright, I.J., Cavender-Bares, J., Craine, J.M., Oleksyn, J., Westoby, M., Walters, M.B., 2003.
1541 The evolution of plant functional variation: traits, spectra, and strategies. *Int. J. Plant Sci.* 164,
1542 S143–S164 ST–The evolution of plant functional. <https://doi.org/10.1086/374368>
- 1543 Reu, B., Proulx, R., Bohn, K., Dyke, J.G., Kleidon, A., Pavlick, R., Schmidlein, S., 2010. The role of
1544 climate and plant functional trade-offs in shaping global biome and biodiversity patterns. *Glob. Ecol.*
1545 *Biogeogr.* 20, 570–581. <https://doi.org/10.1111/j.1466-8238.2010.00621.x>
- 1546 Reu, B., Zaehle, S., Proulx, R., Bohn, K., Kleidon, A., Pavlick, R., Schmidlein, S., 2011. The role of plant
1547 functional trade-offs for biodiversity changes and biome shifts under scenarios of global climatic
1548 change. *Biogeosciences* 8, 1255–1266. <https://doi.org/10.5194/bg-8-1255-2011>
- 1549 Rinaldi, A., Montalto, V., Manganaro, A., Mazzola, A., Mirto, S., Sanfilippo, M., Sarà, G., Sara, G., 2014.
1550 Predictive mechanistic bioenergetics to model habitat suitability of shellfish culture in coastal lakes.
1551 *Estuar. Coast. Shelf Sci.* 144, 89–98. <https://doi.org/10.1016/j.ecss.2014.04.013>
- 1552 Roelke, D.L., Spatharis, S., 2015a. Phytoplankton succession in recurrently fluctuating environments.
1553 *PLoS One* 10, 1–17. <https://doi.org/10.1371/journal.pone.0121392>

- 1554 Roelke, D.L., Spatharis, S., 2015b. Phytoplankton assemblage characteristics in recurrently fluctuating
1555 environments. *PLoS One* 10, 1–25. <https://doi.org/10.1371/journal.pone.0120673>
- 1556 Rosenfield, M.F., Müller, S.C., 2017. Predicting restored communities based on reference ecosystems
1557 using a trait-based approach. *For. Ecol. Manage.* 391, 176–183.
1558 <https://doi.org/10.1016/j.foreco.2017.02.024>
- 1559 Sakschewski, B., von Bloh, W., Boit, A., Rammig, A., Kattge, J., Poorter, L., Peñuelas, J., Thonicke, K.,
1560 2015. Leaf and stem economics spectra drive diversity of functional plant traits in a dynamic global
1561 vegetation model. *Glob. Chang. Biol.* 21, 2711–2725. <https://doi.org/10.1111/gcb.12870>
- 1562 Salguero-Gómez, R., Violle, C., Gimenez, O., Childs, D., 2018. Delivering the promises of trait-based
1563 approaches to the needs of demographic approaches, and vice versa. *Funct. Ecol.* 32, 1424–1435.
1564 <https://doi.org/10.1111/1365-2435.13148>
- 1565 Santini, L., Cornulier, T., Bullock, J.M., Palmer, S.C.F., White, S.M., Hodgson, J.A., Bocedi, G., Travis,
1566 J.M.J., 2016. A trait-based approach for predicting species responses to environmental change from
1567 sparse data: how well might terrestrial mammals track climate change? *Glob. Chang. Biol.* 22, 2415–
1568 2424. <https://doi.org/10.1111/gcb.13271>
- 1569 Savage, V., Webb, C.T., Norberg, J., 2007. Biodiversity on Ecosystem Functioning. *Theor. Biol.* 247,
1570 213–229.
- 1571 Scheffer, M., Baveco, J.M., DeAngelis, D.L., Rose, K.A., van Nes, E.H., 1995. Super-individuals a simple
1572 solution for modelling large populations on an individual basis. *Ecol. Modell.* 80, 161–170.
1573 [https://doi.org/10.1016/0304-3800\(94\)00055-M](https://doi.org/10.1016/0304-3800(94)00055-M)
- 1574 Scheiter, S., Higgins, S.I., 2009. Impacts of climate change on the vegetation of Africa: An adaptive
1575 dynamic vegetation modelling approach. *Glob. Chang. Biol.* 15, 2224–2246.
1576 <https://doi.org/10.1111/j.1365-2486.2008.01838.x>
- 1577 Scheiter, S., Langan, L., Higgins, S.I., 2013. Next-generation dynamic global vegetation models: learning
1578 from community ecology. *New Phytol.* 198, 957–69. <https://doi.org/10.1111/nph.12210>
- 1579 Scherer, C., Jeltsch, F., Grimm, V., Blaum, N., 2016. Merging trait-based and individual-based modelling:
1580 An animal functional type approach to explore the responses of birds to climatic and land use
1581 changes in semi-arid African savannas. *Ecol. Modell.* 326, 75–89.
1582 <https://doi.org/10.1016/j.ecolmodel.2015.07.005>
- 1583 Schirpke, U., Kohler, M., Leitinger, G., Fontana, V., Tasser, E., Tappeiner, U., 2017. Future impacts of

- 1584 changing land-use and climate on ecosystem services of mountain grassland and their resilience.
1585 *Ecosyst. Serv.* 26, 79–94. <https://doi.org/10.1016/j.ecoser.2017.06.008>
- 1586 Schleuning, M., Fründ, J., García, D., 2015. Predicting ecosystem functions from biodiversity and
1587 mutualistic networks: An extension of trait-based concepts to plant-animal interactions. *Ecography*
1588 (Cop.). 38, 380–392. <https://doi.org/10.1111/ecog.00983>
- 1589 Schliep, E.M., Gelfand, A.E., Mitchell, R.M., Aiello-Lammens, M.E., Silander, J.A., 2018. Assessing the
1590 joint behaviour of species traits as filtered by environment. *Methods Ecol. Evol.* 9, 716–727.
1591 <https://doi.org/10.1111/2041-210X.12901>
- 1592 Schlossberg, S., Chase, M.J., Griffin, C.R., 2018. Using species traits to predict detectability of animals on
1593 aerial surveys: *Ecol. Appl.* <https://doi.org/10.1002/eap.1632>
- 1594 Schnedler-Meyer, N.A., Mariani, P., Kiørboe, T., 2016. The global susceptibility of coastal forage fish to
1595 competition by large jellyfish. *Proc. R. Soc. B Biol. Sci.* 283. <https://doi.org/10.1098/rspb.2016.1931>
- 1596 Schrum, C., Alekseeva, I., St. John, M., 2006. Development of a coupled physical-biological ecosystem
1597 model ECOSMO. Part I: Model description and validation for the North Sea. *J. Mar. Syst.* 61, 79–
1598 99. <https://doi.org/10.1016/j.jmarsys.2006.01.005>
- 1599 Seifan, M., Seifan, T., Jeltsch, F., Tielbörger, K., 2012. Combined disturbances and the role of their spatial
1600 and temporal properties in shaping community structure. *Perspect. Plant Ecol. Evol. Syst.* 14, 217–
1601 229. <https://doi.org/10.1016/j.ppees.2011.11.003>
- 1602 Seifan, M., Seifan, T., Schiffers, K., Jeltsch, F., Tielbörger, K., 2013. Beyond the Competition-
1603 Colonization Trade-Off: Linking Multiple Trait Response to Disturbance Characteristics. *Am. Nat.*
1604 181, 151–160. <https://doi.org/10.1086/668844>
- 1605 Shea, C.P., Bettoli, P.W., Potoka, K.M., Saylor, C.F., Shute, P.W., 2015. Use of Dynamic Occupancy
1606 Models to Assess the Response of Darters (Teleostei: Percidae) to Varying Hydrothermal Conditions
1607 in a Southeastern United States Tailwater. *River Res. Appl.* 31, 676–691.
1608 <https://doi.org/10.1002/rra.2766>
- 1609 Shephard, S., Fung, T., Houle, J.E., Farnsworth, K.D., Reid, D.G., Rossberg, A.G., 2012. Size-selective
1610 fishing drives species composition in the Celtic Sea. *ICES J. Mar. Sci.* 69, 223–234.
1611 <https://doi.org/10.1093/icesjms/fsr200>
- 1612 Shipley, B., Laughlin, D.C., Sonnier, G., Otfinowski, R., 2011. A strong test of the maximum entropy
1613 model of trait- based community assembly. *Ecology* 92, 507–517. <https://doi.org/10.1890/10-0394.1>

- 1614 Shipley, B., Vile, D., Garnier, E., 2006. From Plant Traits to Plant Communities: A Statistical Mechanistic
1615 Approach to Biodiversity. *Science* (80-.). 314, 812–814. <https://doi.org/10.1126/science.1131344>
- 1616 Shocket, M.S., Strauss, A.T., Hite, J.L., Šljivar, M., Civitello, D.J., Duffy, M.A., Cáceres, C.E., Hall, S.R.,
1617 2018. Temperature Drives Epidemics in a Zooplankton-Fungus Disease System: A Trait-Driven
1618 Approach Points to Transmission Via Host Foraging. *Am. Nat.* 191, 000–000.
1619 <https://doi.org/10.1086/696096>
- 1620 Smallegange, I.M., Ens, H.M., 2018. Trait-based predictions and responses from laboratory mite
1621 populations to harvesting in stochastic environments. *J. Anim. Ecol.* 87, 893–905.
1622 <https://doi.org/10.1111/1365-2656.12802>
- 1623 Smeti, E., Roelke, D.L., Tsirtsis, G., Spatharis, S., 2018. Species extinctions strengthen the relationship
1624 between biodiversity and resource use efficiency. *Ecol. Modell.* 384, 75–86.
1625 <https://doi.org/10.1016/j.ecolmodel.2018.06.006>
- 1626 Smith, B., Prentice, I.C., Climate, M.T.S., Sykes, M.T., 2001. Representation of vegetation dynamics in
1627 the modelling of terrestrial ecosystems : comparing two contrasting approaches within European
1628 climate space. *Glob. Ecol. Biogeogr.* 10, 621–637. [https://doi.org/10.1046/j.1466-](https://doi.org/10.1046/j.1466-822X.2001.00256.x)
1629 [822X.2001.00256.x](https://doi.org/10.1046/j.1466-822X.2001.00256.x)
- 1630 Smith, S.L., Merico, A., Hohn, S., Brandt, G., 2014. Sizing-up nutrient uptake kinetics: Combining a
1631 physiological trade-off with size-scaling of phytoplankton traits. *Mar. Ecol. Prog. Ser.* 511, 33–39.
1632 <https://doi.org/10.3354/meps10903>
- 1633 Song, H.-S., Thomas, D.G., Stegen, J.C., Li, M., Liu, C., Song, X., Chen, X., Fredrickson, J.K., Zachara,
1634 J.M., Scheibe, T.D., 2017. Regulation-Structured Dynamic Metabolic Model Provides a Potential
1635 Mechanism for Delayed Enzyme Response in Denitrification Process. *Front. Microbiol.* 8, 1–12.
1636 <https://doi.org/10.3389/fmicb.2017.01866>
- 1637 Sonnier, G., Shipley, B., Navas, M.L., 2010. Plant traits, species pools and the prediction of relative
1638 abundance in plant communities: A maximum entropy approach. *J. Veg. Sci.* 21, 318–331.
1639 <https://doi.org/10.1111/j.1654-1103.2009.01145.x>
- 1640 Sterck, F., Markesteijn, L., Schieving, F., Poorter, L., 2011. Functional traits determine trade-offs and
1641 niches in a tropical forest community. *Proc. Natl. Acad. Sci.* 108, 20627–20632.
1642 <https://doi.org/10.1073/pnas.1106950108>
- 1643 Sterck, F., Markesteijn, L., Toledo, M., Schieving, F., Poorter, L., 2014. Sapling performance along

- 1644 resource gradients drives tree species distributions within and across tropical forests. *Ecology* 95,
1645 2514–2525. <https://doi.org/10.1890/13-2377.1>
- 1646 Sterck, F., Schieving, F., 2011. Modelling functional trait acclimation for trees of different height in a
1647 forest light gradient: Emergent patterns driven by carbon gain maximization. *Tree Physiol.* 31, 1024–
1648 1037. <https://doi.org/10.1093/treephys/tpr065>
- 1649 Strauss, A.T., Civitello, D.J., Cáceres, C.E., Hall, S.R., 2015. Success, failure and ambiguity of the
1650 dilution effect among competitors. *Ecol. Lett.* 18, 916–926. <https://doi.org/10.1111/ele.12468>
- 1651 Suding, K.N., Goldstein, L.J., 2008. Testing the Holy Grail framework: Using functional traits to predict
1652 ecosystem change. *New Phytol.* 180, 559–562. <https://doi.org/10.1111/j.1469-8137.2008.02650.x>
- 1653 Taffs, R., Aston, J.E., Briley, K., Jay, Z., Klatt, C.G., McGlynn, S., Mallette, N., Montross, S., Gerlach,
1654 R., Inskeep, W.P., Ward, D.M., Carlson, R.P., 2009. In Silico approaches to study mass and energy
1655 flows in microbial consortia: A syntrophic case study. *BMC Syst. Biol.* 3, 1–16.
1656 <https://doi.org/10.1186/1752-0509-3-114>
- 1657 Tanaka, Y., 2012. Trait response in communities to environmental change: Effect of interspecific
1658 competition and trait covariance structure. *Theor. Ecol.* 5, 83–98. <https://doi.org/10.1007/s12080-010-0100-2>
- 1660 Taubert, F., Frank, K., Huth, A., 2012. A review of grassland models in the biofuel context. *Ecol. Modell.*
1661 245, 84–93. <https://doi.org/10.1016/j.ecolmodel.2012.04.007>
- 1662 Tenan, S., Brambilla, M., Pedrini, P., Sutherland, C., 2017. Quantifying spatial variation in the size and
1663 structure of ecologically stratified communities. *Methods Ecol. Evol.* 8, 976–984.
1664 <https://doi.org/10.1111/2041-210X.12719>
- 1665 Terseleer, N., Bruggeman, J., Lancelot, C., Gypens, N., 2014. Trait-based representation of diatom
1666 functional diversity in a plankton functional type model of the eutrophied southern north sea.
1667 *Limnol. Oceanogr.* 59, 1958–1972. <https://doi.org/10.4319/lo.2014.59.6.1958>
- 1668 Thomas, F.M., Vesk, P.A., 2017a. Are trait-growth models transferable? Predicting multi-species growth
1669 trajectories between ecosystems using plant functional traits. *PLoS One* 12, 1–19.
1670 <https://doi.org/10.1371/journal.pone.0176959>
- 1671 Thomas, F.M., Vesk, P.A., 2017b. Growth races in The Mallee: Height growth in woody plants examined
1672 with a trait-based model. *Austral Ecol.* 42, 790–800. <https://doi.org/10.1111/aec.12501>

- 1673 Treseder, K.K., 2016. Model behavior of arbuscular mycorrhizal fungi: Predicting soil carbon dynamics
1674 under climate change. *Botany* 1–25. <https://doi.org/10.1099/vir.0.82772-0>. Functional
- 1675 Van Bellen, S., Mauquoy, D., Payne, R.J., Roland, T.P., Hughes, P.D.M., Daley, T.J., Loader, N.J., Street-
1676 Perrott, F.A., Rice, E.M., Pancotto, V.A., 2017. An alternative approach to transfer functions?
1677 Testing the performance of a functional trait-based model for testate amoebae. *Palaeogeogr.*
1678 *Palaeoclimatol. Palaeoecol.* 468, 173–183. <https://doi.org/10.1016/j.palaeo.2016.12.005>
- 1679 van Benthem, K.J., Froy, H., Coulson, T., Getz, L.L., Oli, M.K., Ozgul, A., 2017. Trait–demography
1680 relationships underlying small mammal population fluctuations. *J. Anim. Ecol.* 86, 348–358.
1681 <https://doi.org/10.1111/1365-2656.12627>
- 1682 Van Bodegom, P.M., Douma, J.C., Witte, J.P.M.M., Ordoñez, J.C., Bartholomeus, R.P., Aerts, R., 2012.
1683 Going beyond limitations of plant functional types when predicting global ecosystem-atmosphere
1684 fluxes: exploring the merits of traits-based approaches. *Glob. Ecol. Biogeogr.* 21, 625–636.
1685 <https://doi.org/10.1111/j.1466-8238.2011.00717.x>
- 1686 Verheijen, L.M., Brovkin, V., Aerts, R., Bönisch, G., Cornelissen, J.H.C., Kattge, J., Reich, P.B., Wright,
1687 I.J., Van Bodegom, P.M., 2013. Impacts of trait variation through observed trait-climate
1688 relationships on performance of an Earth system model: A conceptual analysis. *Biogeosciences* 10,
1689 5497–5515. <https://doi.org/10.5194/bg-10-5497-2013>
- 1690 Vindenes, Y., Edeline, E., Ohlberger, J., Langangen, Ø., Winfield, I.J., Stenseth, N.C., Vøllestad, L.A.,
1691 2014. Effects of Climate Change on Trait-Based Dynamics of a Top Predator in Freshwater
1692 Ecosystems. *Am. Nat.* 183, 243–256. <https://doi.org/10.1086/674610>
- 1693 Violle, C., Enquist, B.J., McGill, B.J., Jiang, L., Albert, C.H., Hulshof, C., Jung, V., Messier, J., 2012.
1694 The return of the variance: Intraspecific variability in community ecology. *Trends Ecol. Evol.* 27,
1695 244–252. <https://doi.org/10.1016/j.tree.2011.11.014>
- 1696 Violle, C., Navas, M.L., Vile, D., Kazakou, E., Fortunel, C., Hummel, I., Garnier, E., 2007. Let the
1697 concept of trait be functional! *Oikos* 116, 882–892. <https://doi.org/10.1111/j.2007.0030->
1698 1299.15559.x
- 1699 Walker, A.P., Quaipe, T., van Bodegom, P.M., De Kauwe, M.G., Keenan, T.F., Joiner, J., Lomas, M.R.,
1700 MacBean, N., Xu, C., Yang, X., Woodward, F.I., 2017. The impact of alternative trait-scaling
1701 hypotheses for the maximum photosynthetic carboxylation rate (V_{cmax}) on global gross primary
1702 production. *New Phytol.* 215, 1370–1386. <https://doi.org/10.1111/nph.14623>

- 1703 Webb, C.T., Hoeting, J.A., Ames, G.M., Pyne, M.I., LeRoy Poff, N., 2010. A structured and dynamic
1704 framework to advance traits-based theory and prediction in ecology. *Ecol. Lett.* 13, 267–283.
1705 <https://doi.org/10.1111/j.1461-0248.2010.01444.x>
- 1706 Weiss, L., Jeltsch, F., 2015. The response of simulated grassland communities to the cessation of grazing.
1707 *Ecol. Modell.* 303, 1–11. <https://doi.org/10.1016/j.ecolmodel.2015.02.002>
- 1708 Weiss, L., Pfestorf, H., May, F., Körner, K., Boch, S., Fischer, M., Müller, J., Prati, D., Socher, S.A.,
1709 Jeltsch, F., 2014. Grazing response patterns indicate isolation of semi-natural European grasslands.
1710 *Oikos* 123, 599–612. <https://doi.org/10.1111/j.1600-0706.2013.00957.x>
- 1711 Welsh, M.E., Cronin, J.P., Mitchell, C.E., 2016. The role of habitat filtering in the leaf economics
1712 spectrum and plant susceptibility to pathogen infection. *J. Ecol.* 104, 1768–1777.
1713 <https://doi.org/10.1111/1365-2745.12632>
- 1714 Westoby, M., 1998. A leaf-height-seed (LHS) plant ecology strategy scheme. *Plant Soil* 199, 213–227.
1715 <https://doi.org/10.1023/A:1004327224729>
- 1716 Westoby, M., Falster, D.S., Moles, A.T., Vesk, P.A., Wright, I.J., 2002. Plant Ecological Strategies: Some
1717 Leading Dimensions of Variation Between Species. *Annu. Rev. Ecol. Syst.* 33, 125–159.
1718 <https://doi.org/10.1146/annurev.ecolsys.33.010802.150452>
- 1719 Wieder, W.R., Grandy, A.S., Kallenbach, C.M., Taylor, P.G., Bonan, G.B., 2015. Representing life in the
1720 Earth system with soil microbial functional traits in the MIMICS model. *Geosci. Model Dev.* 8,
1721 1789–1808. <https://doi.org/10.5194/gmd-8-1789-2015>
- 1722 Willis, S.G., Foden, W., Baker, D.J., Belle, E., Burgess, N.D., Carr, J.A., Doswald, N., Garcia, R.A.,
1723 Hartley, A., Hof, C., Newbold, T., Rahbek, C., Smith, R.J., Visconti, P., Young, B.E., Butchart,
1724 S.H.M., 2015. Integrating climate change vulnerability assessments from species distribution models
1725 and trait-based approaches. *Biol. Conserv.* 190, 167–178.
1726 <https://doi.org/10.1016/j.biocon.2015.05.001>
- 1727 Winemiller, K.O., Rose, K.A., 1992. Patterns of life-history in North American: Implications for
1728 Population Regulation. *Can. J. Fish. Aquat. Sci.* 49, 2196–2218. <https://doi.org/10.1139/f92-242>
- 1729 Woodward, F.I., Lomas, M.R., 2004. Vegetation dynamics – simulating responses to climatic change.
1730 *Biol. Rev.* 79, 643–670. <https://doi.org/10.1017/S1464793103006419>
- 1731 Wright, I.J., Reich, P.B., Westoby, M., Ackerly, D.D., Baruch, Z., Bongers, F., Cavender-Bares, J.,
1732 Chapin, T., Cornelissen, J.H.C., Diemer, M., Flexas, J., Garnier, E., Groom, P.K., Gulias, J.,

- 1733 Hikosaka, K., Lamont, B.B., Lee, T., Lee, W., Lusk, C., Midgley, J.J., Navas, M.-L., Niinemets, U.,
1734 Oleksyn, J., Osada, N., Poorter, H., Poot, P., Prior, L., Pyankov, V.I., Roumet, C., Thomas, S.C.,
1735 Tjoelker, M.G., Veneklaas, E.J., Villar, R., 2004. The worldwide leaf economics spectrum. *Nature*
1736 428, 821–827. <https://doi.org/10.1038/nature02403>
- 1737 Yang, Y., Wang, G., Xiong, Y., 2015. The contribution of intraspecific trait variability to plant community
1738 assembly patterns on the niche-neutral continuum. *Pakistan J. Bot.* 47, 1039–1050.
- 1739 Yang, Y., Zhu, Q., Peng, C., Wang, H., Chen, H., 2015. From plant functional types to plant functional
1740 traits: A new paradigm in modelling global vegetation dynamics. *Prog. Phys. Geogr.* 39, 514–535.
1741 <https://doi.org/10.1177/0309133315582018>
- 1742 Yenni, G., Adler, P.B., Morgan Ernest, S.K., 2012. Strong self-limitation promotes the persistence of rare
1743 species. *Ecology* 93, 456–461. <https://doi.org/10.1890/11-1087.1>
- 1744 Zhang, L., Hartvig, M., Knudsen, K., Andersen, K.H., 2014. Size-based predictions of food web patterns.
1745 *Theor. Ecol.* 7, 23–33. <https://doi.org/10.1007/s12080-013-0193-5>
- 1746 Zhang, L., Takahashi, D., Hartvig, M., Andersen, K.H., 2017. Food-web dynamics under climate change.
1747 *Proc. R. Soc. B Biol. Sci.* 284. <https://doi.org/10.1177/1473325009337840>
- 1748 Zhang, L., Thygesen, U.H., Knudsen, K., Andersen, K.H., 2013. Trait diversity promotes stability of
1749 community dynamics. *Theor. Ecol.* 6, 57–69. <https://doi.org/10.1007/s12080-012-0160-6>
- 1750 Zhu, Q., Iversen, C.M., Riley, W.J., Slette, I.J., Vander Stel, H.M., 2016. Root traits explain observed
1751 tundra vegetation nitrogen uptake patterns: Implications for trait-based land models. *J. Geophys.*
1752 *Res. Biogeosciences* 121, 3101–3112. <https://doi.org/10.1002/2016JG003554>
- 1753 Zwart, J.A., Solomon, C.T., Jones, S.E., 2015. Phytoplankton traits predict ecosystem function in a global
1754 set of lakes. *Ecology* 96, 2257–2264. <https://doi.org/10.1890/14-2102.1>
- 1755