

A Practical Guide to Quantifying Ecological Coexistence

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Abstract

Coexistence is simultaneously one of the most fundamental concepts of ecology, and one of the most difficult to define and quantify. A particular challenge is that, despite a well-developed body of research on the subject, several different schools of thought have developed over the past century, leading to multiple independent, and largely isolated, branches of literature with distinct methodologies. Here, we provide a broad overview of the most common concepts and metrics currently used to detect and quantify ecological coexistence. We first introduce four classes of behaviour that describe different aspects of community dynamics: (i) the existence of a feasible steady state, i.e. where all coexisting species retain positive abundances in the long-term in the absence of interference by external forces; (ii) the existence of a local attractor that draws the community towards a feasible steady state from within a restricted set of starting conditions; (iii): the existence of a global attractor that draws the community towards feasible steady states from any non-zero starting condition; and (o) a null transient state, where species abundances vary over time irrespective of steady states and attractors. Next, we explain how these classes of behaviour relate to commonly used metrics for classifying and quantifying coexistence, including analyses of parameter sensitivity, asymptotic return rates, invasion growth rates, and time to extinction. We then discuss the scope and limitations of each of these behavioural classes and corresponding metrics, with a particular focus on applications in empirical systems. Finally, we provide a potential workflow for matching empirical questions to theoretical tools, and present a brief prospectus looking forward to opportunities to better advance and integrate research on quantifying coexistence.

Key words: ecological coexistence, parameter sensitivity, structural stability, asymptotic return rate, invasion growth rate, mutual invasibility, time to extinction, empirically tractable

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1 Introduction

2 Understanding how and when species coexist is one of the primary goals of
3 ecology (MacArthur 1972). Accurate predictions of the circumstances un-
4 der which communities of species are likely to coexist is also a fundamen-
5 tal prerequisite for addressing many of the discipline’s most pressing chal-
6 lenges, with potential applications including effective design of conservation
7 and restoration strategies (Bradshaw 1992), identifying and managing inva-
8 sive species (Moles et al. 2008), estimating rates of biodiversity change and
9 turnover (Newbold et al. 2015, Blowes et al. 2024), and forecasting impacts
10 of global change (Sage 2020, Usinowicz and Levine 2018, Van Dyke et al.
11 2022). However, despite almost a century of theoretical advances in our un-
12 derstanding of coexistence, the field remains largely fractured, resulting in
13 multiple schools of thought with their own distinct definitions for what quali-
14 fies as coexistence, and surprisingly few attempts to reconcile these dominant
15 frameworks and their corresponding metrics (Lawton 1999, Donohue et al.
16 2016).

17 Within the coexistence literature, it has been especially challenging to
18 synthesise insights about coexistence across empirical studies. This challenge
19 arises due to both the literature’s fragmentation in the definitions and metrics
20 used to quantify coexistence, and because existing metrics are often challeng-
21 ing to apply in real world contexts, requiring both empirical and analytical
22 expertise, ample data, and strong theoretical assumptions (Levine et al. 2017,
23 Clark et al. 2019, Spaak et al. 2023). Arguably as a consequence, there are
24 currently no cross-system meta-analyses or “global studies” of coexistence,

25 and surprisingly, little is known about how opportunities for coexistence com-
26 pare across space, time, and species.

27 This review seeks to provide a high-level overview of recent advances in
28 coexistence theory, with the goal of summarising disparate literatures for
29 theoreticians and empiricists alike, both for ecologists new to coexistence, or
30 those who are experts in a given set of classes and metrics for determining
31 coexistence. We aim for the review to highlight strengths and weaknesses be-
32 tween the different threads of the coexistence literature, with an eye towards
33 practical applications in real world systems. We begin with a brief sum-
34 mary of the historical development of coexistence theory and explain how it
35 shaped the modern concept of coexistence (Section 2). Next, we introduce
36 the most common kinds of dynamical behaviour currently used by theorists
37 to describe coexistence (Section 3.1), and, correspondingly, the most common
38 metrics used to identify these behaviours (Section 3.2). We then provide a
39 more detailed discussion of the general challenges that empirical systems pose
40 for efforts to characterise and measure coexistence (Section 4.1). Finally, we
41 present guidelines and a recommended workflow for matching empirical ques-
42 tions to theoretical tools (Section 4.2), and suggest potential ways forward
43 for the practical study of coexistence (Section 4.3).

44 1.1 Glossary

- 45 • **Coexistence:** For the purposes of this review, we broadly use “coexis-
46 tence” to describe the ability of a community of co-occurring species to
47 persist across a defined set of spatial and temporal scales. Most other

48 published sources provide more specific definitions explained below, e.g.
49 related to *steady states* or *stability* – however, these definitions also vary
50 widely across sub-fields and sources. To avoid ambiguity, we therefore
51 refer to the specific kinds of dynamical behaviour described in section
52 3.1 when more precise definitions of coexistence are necessary.

- 53 • **System state:** A measurement of the dynamical variables in a sys-
54 tem at a given moment in time. In ecology, states usually refer to the
55 abundance or biomass of organisms within a community.
- 56 • **Parameters:** Variables that govern the dynamics of states according to
57 an equation, such as a population model – e.g. intrinsic growth rates,
58 carrying capacities, or species interaction coefficients. Unlike states,
59 parameters are constant for a given set of environmental conditions.
- 60 • **Steady State:** A system state or set of states which the system remains
61 within through time in the absence of interference by external forces.
62 Ecological studies often focus on the concept of *equilibria* – e.g. a set
63 of species abundances that remain fixed at a set of single values over
64 time. More generally, *invariant sets* include a wider range of dynamical
65 behavior, describing a set of states that a system will remain within
66 in the absence of external interference. Invariant sets include periodic
67 and quasi-periodic orbits and chaotic motions. This broader definition
68 is especially important for community dynamics such as predator-prey
69 oscillations or bounded chaos. For simplicity, unless specified otherwise,
70 we will use the term “steady state” to refer both to classic equilibria,
71 and to invariant sets more broadly.

- 72 • **Feasibility:** In ecology, feasibility describes a state in which all species
73 in a community have positive abundances (i.e. greater than zero; a self-
74 evident empirical requirement that is sometimes overlooked in models).
75 Note, however, that a feasible state does not necessarily imply a steady
76 state, nor is it necessarily *stable*, e.g. it need not be associated with an
77 *attractor*.
- 78 • **Attractor:** A steady state to which a system can return following
79 externally driven changes to the state variables (e.g. as observed with
80 the “classic” concept of a stable equilibrium). For a *local attractor*,
81 systems only return to steady state if perturbations are sufficiently
82 small (determined by the size and properties of the attractor), whereas
83 for a *global attractor*, all feasible starting states lead to the same steady
84 state. *Permanence* describes systems with global attractors where the
85 corresponding steady state is also feasible.
- 86 • **Necessary and Sufficient Conditions:** For any theoretical outcome,
87 necessary conditions must be met for the outcome to take place, but
88 they do not guarantee that it will. In contrast, a sufficient condition
89 guarantees that an outcome will take place, but does not necessarily
90 need to be met in order for the outcome to occur. For example, the
91 existence of a feasible equilibrium is necessary (but not sufficient) for
92 permanence, whereas permanence is sufficient (but not necessary) for
93 the existence of a feasible equilibrium (Hofbauer and Sigmund 1998).

94 **2 History of Theoretical Development**

95 Coexistence has been a central tenet of population and community ecological
96 theory since the discipline’s earliest beginnings. Efforts to model community
97 dynamics published in rapid succession by Lotka (1925) and Volterra (1926)
98 both discuss coexistence criteria, with Volterra in particular providing a de-
99 tailed theoretical derivation of the necessary conditions for various forms of
100 stable coexistence across different community structures (see definitions in
101 Section 1.1).

102 These early theoretical and empirical findings were immensely influential
103 for subsequent studies of coexistence. In particular, Gause’s empirical tests of
104 Lotka’s and Volterra’s coexistence theories popularised the competitive ex-
105 clusion principle, which hypothesised that in order to coexist, species needed
106 to differ in terms of their biological needs or ecological niches (Gause 1934).
107 This hypothesis inspired a proliferation of empirical studies that sought to
108 identify the biological factors that enabled coexistence for particular groups
109 of species (e.g. MacArthur 1958, Park 1962, Paine 1966). The hypothesis was
110 formalised mathematically by Nicholson (1933), with a later generalization
111 by Levin (1970) who showed that for a large class of models, the number
112 of stably coexisting species could not exceed the number of limiting factors
113 (called “control factors” in Nicholson 1933). These limiting factors are often
114 interpreted as specific resources such as light or nitrogen (e.g. R* theory,
115 Tilman 1982), though Levin was careful to note that they could also repre-
116 sent any combination of variables that had independent effects on species’
117 per-capita growth rates.

118 Levin's and Nicholson's work showed that limiting factors were critical
119 for understanding the conditions under which coexistence was possible – but
120 also that identifying these factors in practice was likely to be “extremely
121 difficult” for at least two reasons (Levin 1970, p. 416). First, although bio-
122 logical systems include many different interacting species and environmental
123 variables, these variables also tend to be highly correlated in observational
124 data – thereby complicating efforts to identify the number of independent di-
125 mensions acting on growth rates (Ellner 1988). Second, because species often
126 exhibit non-linear growth responses to factors such as resource availability or
127 the abundance of competitors, spatial or temporal variability can cause indi-
128 vidual variables to “act” like multiple independent factors, e.g. with periods
129 of low vs. high resource availability differentially affecting different species’
130 growth functions (Levins 1979, Armstrong and McGehee 1980), or changes
131 in the relative availability of limiting resources leading to spatio-temporal
132 variability in species abundances and dominance structures (Tilman 1982).

133 To overcome these challenges, two main paradigms emerged for studying
134 coexistence while circumventing the need to explicitly identify limiting fac-
135 tors: analyses of *asymptotic return rates* and of *invasion growth rates* (Turelli
136 1978) (see Section 3.2 for details). Asymptotic return rates describe the ten-
137 dency of systems to return to steady state following small perturbations, and
138 have their origins in applied mathematics and physics. Their use became
139 popular in ecology following applications by MacArthur and his contempo-
140 raries for analysing competitive interactions (MacArthur 1958, 1970, 1972).
141 The metric proved particularly effective for assessing coexistence in systems
142 with many interacting species or resources (May and MacArthur 1972, May

143 1973) – especially in cases where coexistence emerged as a direct result of
144 these interactions (Holt 1977, Lawlor 1979). An important finding of these
145 studies was that asymptotic recovery in ecological communities is largely
146 governed by the degree to which species interaction coefficients are linearly
147 independent (MacArthur 1970, Chesson 1990a), thus suggesting that empir-
148 ically measuring interaction strengths might be an effective way to predict
149 and classify coexistence in real world settings (May and MacArthur 1972).

150 Analysis of invasion growth rates yielded a practical metric for identifying
151 coexistence that could be estimated analytically, from model simulations,
152 or even in invasion experiments (MacArthur and Levins 1967, Turelli 1978,
153 Chesson and Warner 1981), with the general intuition that, if each species
154 in a community could increase from rarity with other species at equilibrium,
155 then species should generally coexist (though see Pande et al. 2020). Initially,
156 studies stressed that its validity as a test for stable coexistence had “not yet
157 been proven” (Turelli 1981, 1986). Indeed, an uncritical reliance on invasion
158 growth rates has turned out to be mathematically naive (Barabás et al. 2018),
159 though careful and mathematically rigorous justifications would eventually
160 be provided through the development of permanence theory (Hofbauer 1981,
161 Butler and Waltman 1986, Schreiber 2000). These analyses quickly gained
162 in popularity, both because they often yielded simpler, more mathematically
163 tractable predictions than analyses of asymptotic return rates, and because
164 they were better able to account for effects of large disturbances and complex
165 community dynamics, rather than just small perturbations around a static
166 equilibrium (Turelli 1980, 1981).

167 In particular, a ground-breaking series of articles by Peter Chesson lever-

168 aged invasion analyses to catalog the ways in which coexistence can arise as
169 a result of environmental fluctuations across time (Chesson 1994) and space
170 (Chesson 2000b). Chesson’s theories would eventually become the dominant
171 framework used for explaining why species are able to coexist in spatially or
172 temporally variable environments (see Section 3.3 for more details) – to the
173 point that later authors came to refer to his work as “Modern Coexistence
174 Theory” (Mayfield and Levine 2010, HilleRisLambers et al. 2012, Grainger
175 et al. 2019), in an apparent nod to the Modern Evolutionary Synthesis.

176 **3 Current Paradigms and Metrics**

177 Although “classic” approaches for assessing coexistence are still commonly
178 used by ecologists today, many of these methods have been refined to better
179 account for important aspects of real world ecological systems (see discussion
180 in 4.1, below). This methodological diversity has added important tractabil-
181 ity and nuance to coexistence theory, but it also poses a problem: different
182 methods define coexistence in distinct, and sometimes even contradictory
183 ways – and, indeed, often make conflicting predictions (Turelli 1978).

184 To compare and contrast this sea of methods, we first introduce four
185 broad classes of dynamical behaviour that ecologists tend to focus on when
186 studying coexistence (Section 3.1). These behaviours roughly correspond to
187 the different definitions of coexistence (or lack thereof) that are applied in
188 contemporary theoretical studies. We then discuss metrics that are commonly
189 used to identify and quantify each of these four behavioural regimes (Section
190 3.2), as well as their scope and limitations. Challenges associated with ap-

191 plying these metrics in empirical systems are discussed in more detail in the
192 following section (Section 4).

193 **3.1 Classes of Dynamic Behaviour**

194 Species dynamics can be broadly grouped into four main classes of behaviours
195 (Fig. 1). These behaviours are: *(i)* **feasible steady states** – systems that
196 can remain at steady state where all species have positive abundances (3.1.1);
197 *(ii)* **feasible local attractors** – systems with local attractors that draw
198 species towards feasible steady states given a specific set of positive start-
199 ing abundances (3.1.2); *(iii)* **feasible global attractors** – systems with a
200 global attractor that draws species towards some set of feasible steady states
201 (potentially including multiple different local attractors) from any starting
202 condition with a set of non-zero species abundances (3.1.3); and, finally, *(o)*
203 **transient states** – a state in which species abundances vary over time either
204 without or prior to settling into a steady state that may or may not yield
205 coexistence (3.1.4).

206 Each of these behaviours relates to somewhat different aspects of coex-
207 istence and stability. In practical terms for real world communities: *(i)* a
208 feasible steady state implies that species will persist together in the long-
209 term so long as they remain undisturbed by external forces; *(ii)* a local
210 attractor implies that species can recover back to a steady state following
211 small disturbances of the population abundances; *(iii)* a global attractor im-
212 plies that the community can recover even from large disturbances; and *(o)*
213 transient dynamics imply that the system is in transition, and species will

214 either eventually go extinct or the system's dynamical behaviour will switch
215 to one of the three other regimes. In the absence of demographic stochas-
216 ticity (see Section 4.1.3), behaviours *i-iii* also follow something of a nested
217 hierarchy: a feasible steady state is a necessary (but not sufficient) condition
218 for a feasible local attractor, which is itself a necessary (but again, not suffi-
219 cient) condition for a feasible global attractor. We compare these dynamics
220 to transient systems, as transient dynamics can maintain co-occurrence on
221 ecologically relevant timescales, even if long-term coexistence and stability
222 are not expected. Below, we introduce these behaviours in more detail.

223 **3.1.1 Feasible Steady State**

224 A feasible steady state describes conditions for which coexisting species'
225 abundances remain at fixed positive values over time (when at an equilib-
226 rium) or constrained within a given set of positive values (for invariant sets
227 more generally, e.g. limit cycles). An intuitive example is carrying capacity in
228 the logistic growth model – if a single species begins at its carrying capacity,
229 then it will remain there in the absence of interference by external forces.
230 Feasible steady states are necessary for long-term coexistence (although they
231 do not guarantee it). Thus, the breakdown of a feasible steady state implies
232 either extinction of some species, or that the system will become transient
233 as it moves towards some other dynamical regime. In theoretical models,
234 testing for feasible steady states is usually the first step before subsequent
235 analyses of *stable* coexistence can proceed (Dormann 2008). This step is im-
236 portant not only because negative abundances are logically impossible, but
237 also because they can produce nonsensical effects in models – e.g. in the gen-

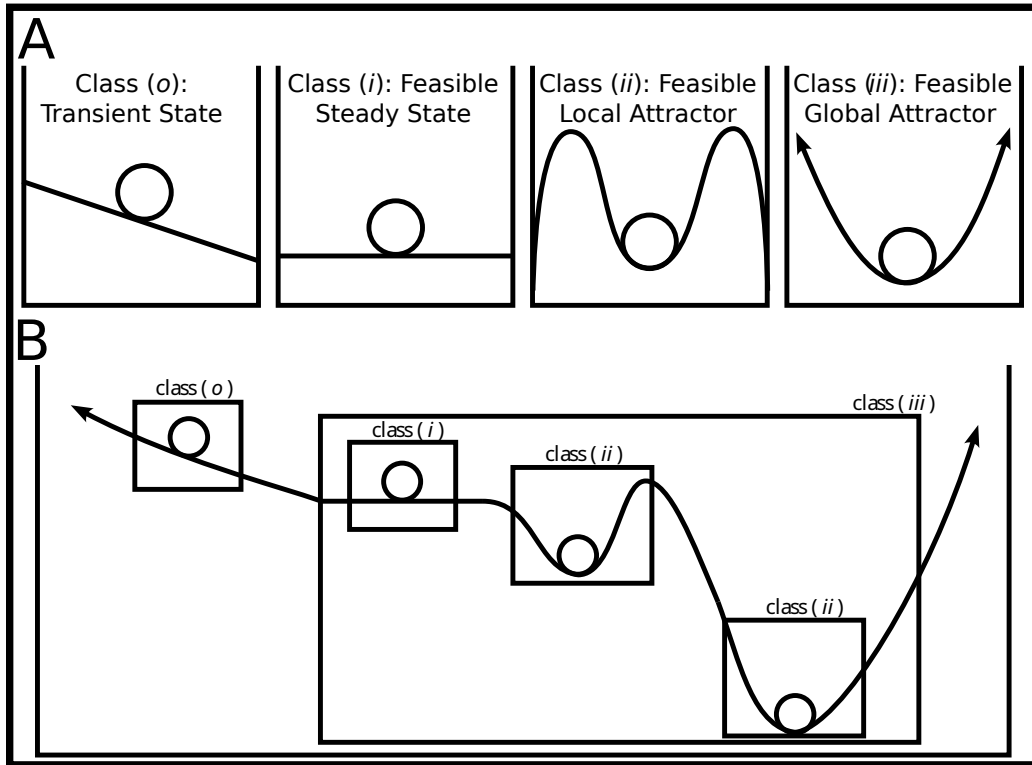


Figure 1: Four main classes of behaviour describing species abundance dynamics in the context of coexistence. **(a)** Conceptual illustration of abundance dynamics following each of the four behaviour classes discussed in Section 3.1, using a ball-and-cup metaphor. The position of the ball represents the system state (e.g. the abundance of a particular species), and the rolling trajectories in panels *o-iii* represent a lack of steady state, the presence of a feasible steady state, a feasible local attractor, and a feasible global attractor, respectively. Arrows around the global attractor in class *iii* indicate that the landscape extends infinitely in both directions. **(b)** An example dynamic landscape combining all four of the classes of behaviour as part of a single system. Note that dynamical behaviours within subsections of the system can follow different combinations of behaviours *o-ii*. The feasible steady states in class *i* plus the two feasible local attractors in class *ii* jointly make up the system's global attractor (class *iii*). In this example, in the long-term, the system is drawn away from transience and towards at least one of these states from any feasible starting state, with the precise end-state dependent on initial conditions.

238 eralised Lotka-Volterra equations, a competitor with negative abundance has
239 the same effect on other species' per-capita growth rates as a mutualist with
240 positive abundance.

241 Especially in models that include many different potential steady states
242 (such as alternate stable states; see the two boxes labelled “class (*ii*)” in Fig.
243 1B), testing for feasibility can be laborious, as it requires first recognising
244 and discarding all infeasible steady states that include negative abundances
245 (Anderson et al. 1992, AlAdwani and Saavedra 2020, 2022). Nevertheless,
246 identifying feasibility criteria can sometimes be more analytically tractable
247 than other coexistence metrics (e.g. testing for the existence of an attrac-
248 tor), which has led to the use of feasibility as an independent proxy for the
249 possibility of coexistence in some studies (Saavedra et al. 2017, Grilli et al.
250 2017, Song et al. 2018, see Section 3.2.1 for more details). Although most
251 of these studies of feasible coexistence have focused on equilibria, these ap-
252 proaches sometimes can be applied to more complex invariant sets – e.g. to
253 identify ranges of model parameters that lead to oscillatory cycles or even
254 chaos (Barabás et al. 2012, Barabás and Ostling 2013, Bunin 2017, McCann
255 and Yodzis 1994).

256 **3.1.2 Feasible Local Attractor**

257 Local attractors ensure that some range of starting conditions exist from
258 which the system will be drawn towards a steady state. This range of start-
259 ing conditions is called the “basin of attraction” of the attractor, and is often
260 visualised as valleys in classical ball-and-cup diagrams such as Figure 1. Fea-
261 sible local attractors support coexistence by counteracting interference by

262 external forces, such as small environmental perturbations, that might oth-
263 erwise drive species away from a feasible steady state, and towards extinction.
264 Indeed, in the absence of an attractor, a sequence of arbitrarily small pertur-
265 bations will, in the long-term, drive species to extinction (Schreiber 2006).
266 Local attractors, however, only predict dynamics in the range of starting
267 conditions from which the system tends towards the attractor. Thus, the ex-
268 istence of a feasible local attractor does not necessarily guarantee long-term
269 coexistence – e.g. if initial abundances fall outside of the range of influence
270 of that attractor (i.e. outside of the surrounding “valley” in the ball-and-cup
271 diagram), or species are subjected to sufficiently strong perturbations, then
272 long-term abundance dynamics can be driven away from the initial steady
273 state, and towards other system states, such as those associated with alter-
274 nate community structures or even species extinction (Almaraz et al. 2024).

275 Although the tractability and accuracy of different approaches for study-
276 ing local attractors can vary, they all essentially share the same goal: to
277 characterise dynamics around steady states based on their asymptotic re-
278 turn rates, and extrapolate whether dynamics are likely to remain in that
279 state or to move towards another dynamical regime (Turelli 1978). Early
280 work by Lewontin (1969), Levin (1970), MacArthur (1970), and May (1973),
281 for example, identified local attractors by computing the eigenvalues for the
282 Jacobian matrix near model equilibria. These approaches are still popular
283 today, and are discussed in more detail in Section 3.2.2. For more general
284 classes of invariant sets (e.g. oscillatory dynamics, chaos), local attractors
285 can be identified by calculating return rates along the entirety of the sys-
286 tem’s dynamical trajectory, e.g. via bifurcation analysis or using Lyapunov

287 exponents. These approaches are discussed in Section 3.2.2.1.

288 **3.1.3 Feasible Global Attractor**

289 In ecology, feasible global attractors refer to system dynamics in which a set
290 of species are drawn towards feasible steady states from any feasible starting
291 abundance – thereby meeting the criteria for *permanence*. Feasible global
292 attractors therefore ensure long-term coexistence even in the face of strong
293 disturbances and major re-mixing of a community. So long as perturbations
294 do not push a species to an abundance of zero, they will always be able to
295 recover in the long-run. This strong form of coexistence comes at the cost of
296 more strict requirements for feasible global attractors to even exist. Indeed,
297 their existence necessarily excludes several classes of behaviours that might
298 be considered “coexistence” under other definitions. For example, systems
299 subject to Allee effects – where species must exceed some minimum abun-
300 dance to achieve positive growth (Fukami and Nakajima 2011, Jang 2013)
301 – preclude feasible global attractors, as do systems where co-occurrence is
302 transient, even if it is long-lasting.

303 The especially broad scope of global attractors also comes with technical
304 challenges. Identifying and testing for them can be difficult, but invasion
305 analysis was introduced as a more tractable approach for identifying these
306 global attractors (Turelli 1978, Hofbauer 1981, Schreiber 2000). The general
307 idea behind invasion analysis is that if all species in a community can increase
308 in abundance when rare, then the system should be able to recover from
309 most kinds of major disturbances – and that this behaviour is, at the very
310 least, consistent with the existence of a feasible global attractor (e.g. Turelli

311 1981, 1986, though see Barabás et al. 2018 for theoretical limitations and
312 Schreiber 2000, Hofbauer and Schreiber 2022 for some counterexamples).
313 The development of permanence theory in the early 1980's provided more
314 rigorous mathematical justification for these approaches, summarising the
315 circumstances under which invasion analyses are sufficient for proving the
316 existence of a global attractor (Hofbauer 1981, Butler and Waltman 1986,
317 Garay 1989, Schreiber 2000). Analyses of invasion growth rates remain in
318 wide use today and are discussed in more detail in Section 3.2.3.

319 **3.1.4 Transient State**

320 In ecology, transient states refer to abundance dynamics varying either before,
321 or without, reaching a steady state (Hastings 2004, Fukami and Nakajima
322 2011). Transient dynamics can be short or long-lasting, and may or may not
323 ultimately drive communities towards feasible steady states in the long run
324 – although in the absence of feasible steady states, the long-term fate of any
325 species is extinction (Murdoch 1994). In practice, it can be challenging to
326 determine whether a particular dynamical trajectory is truly transient, is in
327 a basin of attraction, or is even part of some more complex invariant set such
328 as a limit cycle. Due to this ambiguity, categorising something as a transient
329 state usually implies that no steady states that influence the current state
330 have *yet* been identified, but often does not definitively exclude the possibility
331 of their existence.

332 **3.2 Metrics for Characterising Behaviours**

333 Most contemporary studies rely on metrics that quantify specific aspects of
334 coexistence, rather than focusing on general classes of dynamical behaviours
335 themselves. The most widely used of these include: *(i)* **parameter sensitiv-**
336 **ity** – the quantification of how slight changes in parameter values alter sys-
337 tem attributes, such as the existence and identity of species in feasible steady
338 states (3.2.1); *(ii)* **asymptotic return rate** – the rate at which systems are
339 drawn towards or away from a particular steady state (3.2.2); *(iii)* **invasion**
340 **growth rate** – the rate at which species are able to increase from low abun-
341 dance (3.2.3); and *(o)* **time to extinction** – the average length of time for
342 which species maintain positive population sizes (3.2.4). Importantly, each of
343 these metrics relates to one or more of the dynamical behaviours discussed
344 in Section 3.1: parameter sensitivity is useful for assessing the robustness of
345 steady states to uncertainty in, or perturbations to, parameter values; asymp-
346 totic return rates can be used to identify local attractors; invasion growth
347 rates can be applied to test for the existence of a feasible global attractor;
348 and time to extinction can be calculated for any kind of abundance dynamic,
349 including transient states that yield co-occurrence on ecologically relevant
350 timescales (Fig. 2). Below, we introduce these metrics in more detail, with a
351 particular focus on how they are applied in practice.

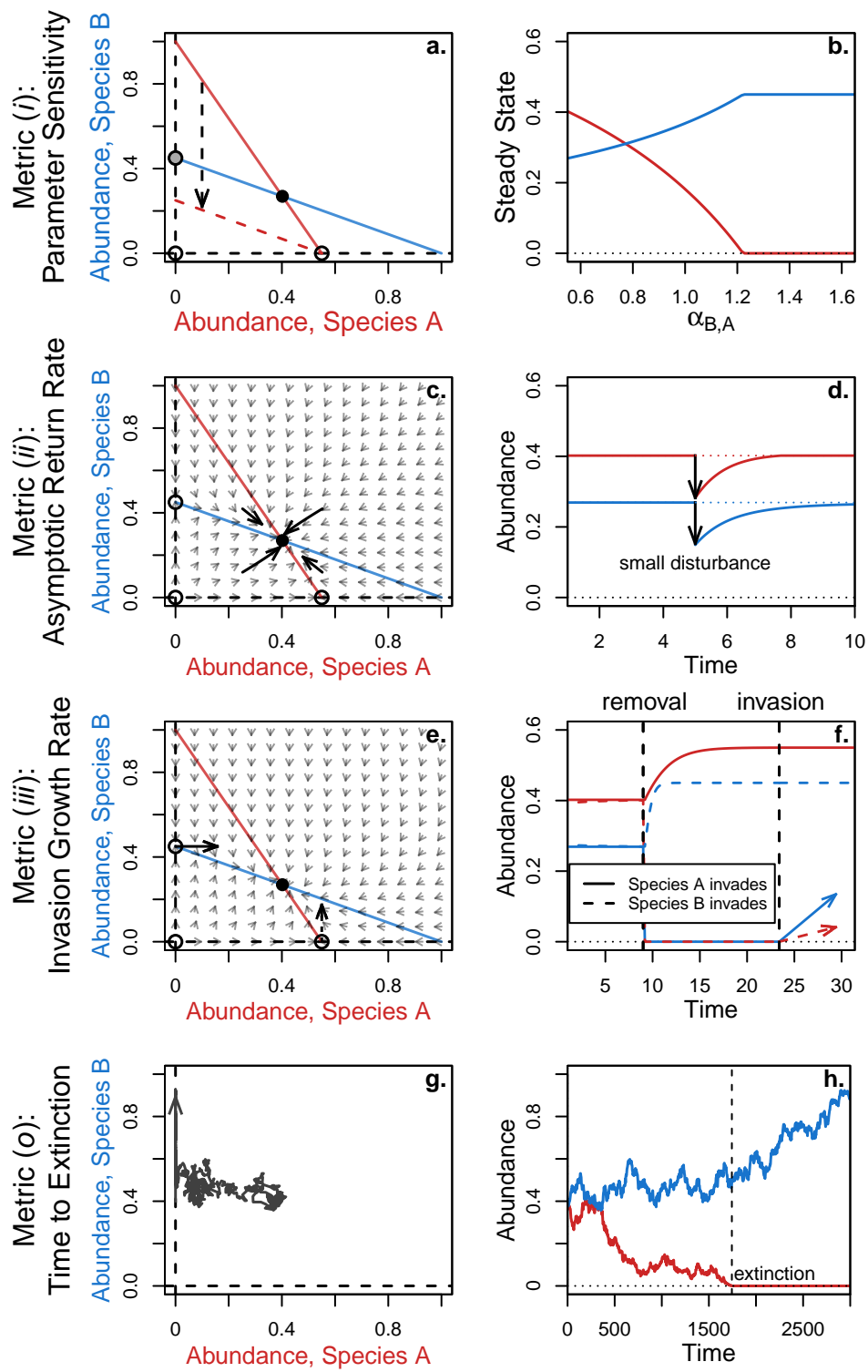


Figure 2: Caption on next page.

Figure 2: Conceptual illustration of the coexistence metrics in Section 3.2. Left column shows phase diagrams. Red and blue lines, respectively, show abundances at which species A and B experience zero net growth (“zero net growth isoclines”); empty circles show unstable equilibria; and filled circles show feasible attractors. Black arrows emphasise the main dynamics of interest for each metric. Right column shows corresponding time-series (b, f, h) or impacts of parameter changes (d), for each species. Time to extinction (o) is shown for a random walk with two species (thick black line and arrow). Remaining panels show results for the two-species Lotka-Volterra competition equations. Parameter sensitivity (i) is demonstrated via changes in $\alpha_{B,A}$, which describes the impact of species B on the per-capita growth rate of species A. The black dashed arrow shows the shift in the isocline associated with the parameter change, shifting the solid red isocline to the dashed red and causing a previously unstable equilibria to become stable (light grey circle). Asymptotic return rates (ii) are demonstrated in response to a series of small perturbations around the feasible equilibrium – small grey arrows show the gradient of the system’s dynamics, and the thick black arrows show return trajectories. Invasion growth rates (iii) are shown with solid and dashed arrows at the time of invasion, representing growth trajectories starting from low abundance for species A and B, respectively, with the competitor species at its single-species carrying capacity.

352 3.2.1 Parameter Sensitivity

353 Parameter sensitivity is related to the general mathematical concept of “struc-
 354 tural stability,” which focuses on whether the topological features of a dy-
 355 namical system are preserved under small perturbations of its underlying
 356 equations or parameter values (Smale 1967, Levin 1970). Structural stabil-
 357 ity can be applied in studies of coexistence to examine the conditions under
 358 which global attractors break down into local attractors, or to identify critical
 359 points where small changes in parameters alter the system’s stability, such as
 360 switching from an equilibrium to a periodic solution (Almaraz et al. 2024).
 361 In a growing body of ecological studies, however, the concept of structural

362 stability has been defined somewhat more narrowly, to test whether small
363 perturbations to model parameters lead to the breakdown of feasible steady
364 states (Rohr et al. 2014).

365 Having grown out of this focus on steady states, analyses of parameter
366 sensitivity in ecology typically take one of two approaches. The first focuses
367 on the range of model parameter values within which feasible steady states
368 can be maintained for a particular subset of species (May 1973, Svirezhev
369 and Logofet 1983, Grilli et al. 2017, Saavedra et al. 2017, 2020, Deng et al.
370 2022, Allen-Perkins et al. 2023). This approach provides a general overview of
371 which regions of parameter space allow for coexistence and which regions do
372 not. For example, under the Lotka-Volterra competition equations, if species
373 *A* and *B* initially coexist, then increasing the competitive impact of species *B*
374 on species *A* will eventually drive species *A* extinct (Fig. 2a, b). The second
375 approach examines localised effects of perturbations. It takes a known steady
376 state, and examines the sensitivity of that steady state to small parameter
377 perturbations (Vandermeer 1970, Levins 1974, Meszena et al. 2006, Barabas
378 et al. 2014). Steady states that are oversensitive to even very small changes
379 in the parameters (e.g. with a shallow basin of attraction) are not expected
380 to exist for long, and are thus assumed to not allow for coexistence in the
381 long-term. While this second method forgoes giving a global description of
382 coexistence in parameter space, it has key advantages. Most importantly,
383 since it relies on perturbation calculus near a known feasible steady state,
384 it can, in principle, be applied to arbitrarily complicated dynamics (whereas
385 global descriptions are more difficult to generalise across scenarios).

386 If the range of parameters allowing feasible steady states is large, those

387 steady states are said to be “robust” against parameter perturbations. In
388 biological terms, species will have more opportunities to coexist by with-
389 standing a larger range of external environmental changes that impact their
390 parameter values (e.g. growth rates, carrying capacities). This perspective
391 has been especially effective at elucidating how different processes contribute
392 to coexistence – e.g., disentangling how multiple limiting factors contribute
393 to coexistence and rigorously connecting these insights back to species’ eco-
394 logical roles in a way that is independent of model details (Meszéna et al.
395 2006, Barabás et al. 2014, Pásztor et al. 2016), quantifying the relative ef-
396 fects of pairwise vs. indirect interactions on equilibria in the Lotka-Volterra
397 competition equations (Saavedra et al. 2017, García-Callejas et al. 2021),
398 predicting which species have larger persistence times (Allen-Perkins et al.
399 2023, Domínguez-García et al. 2024), or dividing feasibility criteria into sta-
400 bilising and equalising components (Godoy et al. 2018), analogous to classic
401 partitions of invasion growth rates as discussed in Section 3.3.

402 For equilibria, parameter sensitivity can be computed relatively easily
403 – either by identifying combinations of parameter values that lead to zero
404 net population growth for all species in the community, or by simulating the
405 model forward in time until it reaches a feasible equilibrium. However, param-
406 eter sensitivity can also be computed for more complex dynamics (Barabás
407 et al. 2012, Barabás and Ostling 2013, Barabás et al. 2014), or even based
408 on empirically observed time-series data. For example, several recent studies
409 have extended the scope of parameter sensitivity analyses to include effects
410 of large perturbations (Tabi et al. 2020, Medeiros et al. 2021), spatially and
411 temporally structured environments (Saavedra et al. 2020, García-Callejas

412 et al. 2021, Luo et al. 2022, Song et al. 2023, Long et al. 2024), and nonlinear
413 conditions for specifying steady states (Cenci and Saavedra 2018a).

414 **3.2.2 Asymptotic Return Rate**

415 Asymptotic return rates describe the long-term response of a dynamical sys-
416 tem to infinitesimally small perturbations by external forces. In ecological
417 studies of coexistence, asymptotic return rates are usually applied to track
418 the ability of species abundances to return to a particular steady state. If
419 these return rates indicate that the system will always be drawn back to-
420 wards that steady state regardless of the direction of the perturbation, the
421 system is said to be *asymptotically stable* (Fig. 2c, d). Tests of asymptotic
422 stability are analogous to testing for the existence of a local attractor –
423 i.e. proving asymptotic stability is sufficient for identifying a local attractor.
424 Thus, asymptotic stability around a feasible steady state implies coexistence,
425 provided that species initial abundances fall within the region of the local
426 attractor and that interference by external forces is sufficiently small that it
427 does not push species out of this region.

428 For equilibria, asymptotic stability is tested by quantifying the return
429 rates from small perturbations around the equilibrium by computing the
430 eigenvalues of the Jacobian matrix. The details of this procedure are beyond
431 the scope of this review (see Otto and Day 2011 for an excellent introduction),
432 but in essence, eigenvalues summarise rates of change along a set of trans-
433 formed axes (analogous to principal component axes), which make it easier
434 to quantify net effects of different combinations of perturbations and species
435 dynamics. If the eigenvalues indicate that all species are drawn back towards

436 equilibrium following small perturbations, then the system is asymptotically
437 stable. Different indicator criteria must be used depending on the kind of
438 system. For continuous-time systems in which population dynamics play out
439 smoothly over time, e.g. as might be expected for algae or bacteria, the re-
440 turn towards equilibrium occurs if the real part of the leading eigenvalue is
441 negative (i.e. the eigenvalue with the largest non-imaginary component). For
442 discrete-time systems in which population dynamics occur at regular inter-
443 vals, e.g. as might be assumed for annual plants or some insects, the absolute
444 value of the largest eigenvalue in magnitude (the “dominant” eigenvalue)
445 must be less than one. Several studies have also proposed methods for uni-
446 fying the concepts of structural stability (described above) and asymptotic
447 stability as part of a single analysis (Arnoldi and Haegeman 2016, Song and
448 Saavedra 2018, Medeiros et al. 2021) – although these approaches are not yet
449 in wide use.

450 There are several important considerations for interpreting asymptotic re-
451 turn rates. First, eigenvalues alone do not indicate whether a corresponding
452 equilibrium is feasible; as such, equilibria that include non-positive species
453 abundances must be discarded prior to analysis (Dormann 2008, Saavedra
454 et al. 2017). Moreover, assessing only a subset of eigenvalues, or focusing
455 only on their sign but not their magnitude, can give a misleading picture of
456 community dynamics as a whole. This is because species within a community
457 can present different recovery dynamics. For example, the leading eigenvalue
458 – which is often reported as a stand-alone index of asymptotic stability –
459 is primarily determined by the long-term recovery rate for the slowest dy-
460 namical component of the system. Thus, even if only a single rare species

461 fails to recover from a perturbation, the real part of the corresponding lead-
462 ing eigenvalue will still indicate a lack of asymptotic stability for the entire
463 community (Arnoldi et al. 2016, 2018). Similarly, this property can be mis-
464 leading in systems that are subject to repeated perturbations, as the leading
465 eigenvalue typically only includes information on long-term responses, rather
466 than short-term dynamics (Arnoldi et al. 2018).

467 **3.2.2.1 Dynamic approaches for assessing return rates** Real world
468 communities tend to be highly dynamic, which limits the utility of meth-
469 ods that focus on systems near equilibrium (Pimm et al. 2019). Although
470 theoretical methods exist for analysing asymptotic stability in systems with
471 more complex dynamics – e.g. that converge towards invariant sets such as
472 limit cycles or quasi-periodic orbits (Sell 1966, Hirsch et al. 1970, Breunung
473 2022) – applying these metrics in practice can be difficult. The problem is
474 two-fold. First, given an observed dynamical trajectory, it no longer suffices
475 to test asymptotic return rates around a single fixed point – rather, return
476 rates must be calculated along the entirety of that trajectory. Second, even if
477 the observed part of a trajectory can be shown to be an attractor such that
478 nearby states will always converge to it, there is no guarantee that the tra-
479 jectory corresponds to long-term coexistence. For example, given any feasible
480 starting abundance, dynamical trajectories for a logistic growth model with
481 $r < 0$ will converge, but that convergence will be towards extinction rather
482 than coexistence.

483 To address these challenges, an increasingly common approach is to apply
484 forecasting tools such as *empirical dynamic modelling* (EDM) to approximate

485 community dynamics, and then analyse the stability of the resulting model
486 (Sugihara 1994, Deyle et al. 2016). EDM uses time-series observations to fit
487 a series of piecewise locally weighted linear regressions that jointly describe
488 how abundance dynamics, interactions among species, and environmental
489 covariates change over time. Estimates of the Jacobian matrix describing
490 community dynamics at each time step can then be computed directly from
491 these piece-wise regressions. Asymptotic stability is then tested in one of two
492 ways: either individual estimates of the Jacobian matrix are used to iden-
493 tify a potential equilibrium towards which the system is drawn (Ushio et al.
494 2018), or the full set of Jacobian Matrices can be applied to approximate
495 their corresponding “Lyapunov spectrum” (effectively a time-varying gen-
496 eralisation of eigenvalues, which describe return rates along a dynamic tra-
497 jectory) (Oseledec 1968). In addition to assessing asymptotic return rates,
498 these time-varying estimates of the Jacobian matrix can also be used to assess
499 parameter sensitivity, as discussed in 3.2.1 (Cenci and Saavedra 2019). For
500 a more detailed review of EDM, including a discussion of available software
501 for carrying out analyses, see Munch et al. (2022).

502 **3.2.3 Invasion Growth Rates**

503 Invasion growth rates quantify the average per-capita growth rate of a species
504 when it is relatively rare (termed the “invader”), and the rest of the com-
505 munity is at steady state (termed the “resident”). Intuitively, if the invasion
506 growth rate of a species is positive, the species can increase from rarity and,
507 thereby, escape extinction risk at least in the short term if not in the long-
508 term (Case 1995, Arnoldi et al. 2022). Alternatively, if the invasion growth

509 rate of a species is negative, then once a species reaches low abundance,
510 it would decline to extinction under current conditions. Independently in
511 the mathematical literature, invasion growth rates are used to characterise
512 whether coexistence occurs in the sense of a feasible global attractor (also
513 known as permanence or uniform persistence Hofbauer 1981, Schreiber 2000,
514 Patel and Schreiber 2018). Only recently have the more heuristic approaches
515 in the ecological literature and the rigorous approaches in the mathematical
516 literature begun to merge, providing a unique opportunity to simultaneously
517 evaluate whether coexistence in the sense of permanence occurs in a math-
518 ematically rigorous manner, and to probe the mechanisms underlying this
519 coexistence in ecologically meaningful ways.

520 In practice for coexistence analyses, invasion growth rates are frequently
521 used to understand when two competing species could coexist at a global
522 feasible attractor. Invasion growth rates are quantified for both species, and
523 when both of these invasion growth rates are positive, then each species
524 would increase from rarity and thus they would coexist at a global feasible
525 attractor (Fig. 2e, f). This condition for coexistence is known as the “mu-
526 tual invasibility” criterion. The mutual invasibility criterion has been used
527 extensively to assess scenarios that yield coexistence and their corresponding
528 mechanisms (Chesson 1994, Adler et al. 2007, Chesson 2018, Barabás et al.
529 2018, Ellner et al. 2020) (see Section 3.3), and has been extended to com-
530 munities composed of more than two species by assuming that whenever a
531 species became rare, the remaining species would approach a steady state at
532 which their densities are positive. The invasion growth rate of the rare species
533 would be its average per-capita growth rate at this steady state. Provided

534 that invasion growth rates are positive for all species, coexistence at a global
535 feasible attractor is assumed to occur; as we discuss below, this condition is
536 necessary, but not sufficient for coexistence.

537 The mutual invasibility framework has several advantages. First, as long
538 as the removal of the species does not incite any co-extinctions of other
539 species, invasion analysis effectively tests whether each species in a commu-
540 nity can successfully reestablish itself from low density after being driven
541 locally extinct. For this reason, mutual invasibility is often presented as a
542 more biologically meaningful metric in systems that are subject to strong
543 stochastic influences or frequent large disturbances (Turelli 1981). Indeed,
544 mathematical theory for coexistence in the face of environmental stochas-
545 ticity relies almost exclusively on this metric (Schreiber et al. 2011, Hening and
546 Nguyen 2018, Benaïm and Schreiber 2019). Second, because mutual invasi-
547 bility focuses on system dynamics when the focal species is effectively absent
548 from the community, invasion analysis can (at least in theory) ignore feed-
549 backs between the invading species and the rest of the community, which can
550 simplify mathematical analyses, especially if the total number of species in
551 the community is small.

552 In empirical studies, invasion rates are often parameterised using data
553 from pairwise competition experiments, where the fitness (e.g. seed produc-
554 tion) of individuals of a focal species is evaluated along a density gradient of
555 its competitor (Godoy and Levine 2014, Kraft et al. 2015, Wainwright et al.
556 2019). However, these pairwise tests are not necessarily indicative of species'
557 performance in diverse communities, e.g. due to effects of intransitive compe-
558 tition, higher-order interactions, or other emergent mechanisms that stabilise

559 (or destabilise) coexistence only under higher diversity and not in pairwise
560 scenarios (May and Leonard 1975, Edwards and Schreiber 2010, Mayfield
561 and Stouffer 2017, Barabás et al. 2018). As such, an increasingly popular
562 alternative approach is to fit models directly to time-series observations of
563 diverse community dynamics (Ovaskainen et al. 2017) or to natural variation
564 in fitness and neighborhood composition across spatial scales (Lanuza et al.
565 2018). Once parameterised, the model can either be used to estimate invasion
566 rates for each species in the community (Ellner et al. 2020), or fitted param-
567 eter values can be compared to formula describing the necessary or sufficient
568 conditions for mutual invasibility in the model (e.g., if species compete more
569 strongly with themselves than each other) (Broekman et al. 2019). Especially
570 popular models for these applications include the Lotka-Volterra competition
571 equations (Chesson 2018) and various augmentations of the Chesson (1990b)
572 annual plant model – though many other models, such as the MacArthur or
573 Tilman resource competition frameworks have also been analysed (Chesson
574 1990a, Letten et al. 2018). For a more detailed review of these methods, see
575 Grainger et al. (2019), Barabás et al. (2018), and Godwin et al. (2020).

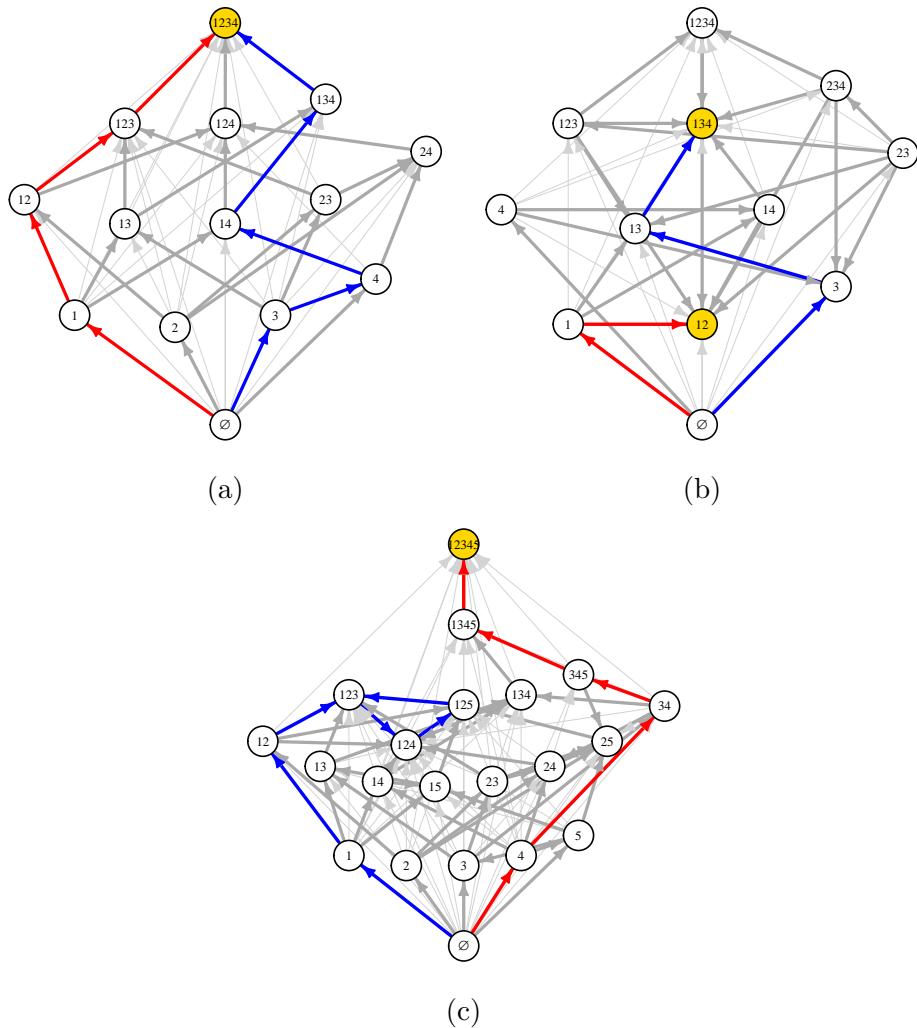


Figure 3: Invasion graphs for three empirically parameterised Lotka-Volterra models. Invasion graph (a) is acyclic and as all subcommunities are invadible, the entire community is permanent (gold vertex). Invasion graph (c) is cyclic with all subcommunities invadible, but requires verifying an additional condition (Schreiber 2000) to ensure permanence of the entire community (gold vertex). Invasion graph (b) is acyclic but has two uninvadible subcommunities (gold vertices) which are non-feasible attractors and, consequently, the entire community is not permanent. The vertices in the graphs correspond to steady states of the Lotka-Volterra model and the directed edges correspond to potential community trajectories connecting the steady states as identified by invasion growth rates. Thick edges correspond to transitions due to single species invasions, while thin edges correspond to transitions due to multiple species additions. The colored edges indicate sequences of single species invasions terminating at an attractor for the model.

576 **3.2.3.1 Permanence theory** A common critique of coexistence anal-
577 yses based on invasion growth rates is that, at least superficially, they seem
578 unable to address important nuances of real world systems. For example,
579 how can invasion rates be calculated for predator and prey species, or for
580 obligate mutualists, where the removal of one species necessarily leads to
581 the extinction of the other – or, what of cases where invasions merely lead
582 to subsequent extinctions, such as in “rock-paper-scissors” models (Barabás
583 et al. 2018)?

584 While in some cases, these concerns have been addressed by model-specific
585 solutions (e.g. Chesson and Kuang 2008, Ke and Wan 2020, Song and Spaak
586 2024), the mathematical theory of permanence (i.e. a global feasible attrac-
587 tor) provides a general approach for addressing these kinds of questions.
588 While the general abstract mathematical theory was developed in the 1980s
589 (Hutson 1984, Butler et al. 1986, Hofbauer and So 1989) with the connection
590 to invasion growth rates made in 2000 (Schreiber 2000), the theory was too
591 technical for general application in ecology (see, however, Law and Morton
592 1996 who used an important special case of this theory; Hofbauer 1981). To
593 help demystify this theory, Hofbauer and Schreiber (2022) introduced inva-
594 sion graphs (Fig. 3). These graphs use invasion growth rates to identify all
595 community trajectories that connect non-feasible steady states (i.e. where
596 at least one species is missing from the community). Provided this invasion
597 graph has no cycles (i.e. no rock-paper-scissor like dynamics), coexistence
598 occurs if and only if, for every non-feasible steady state, at least one missing
599 species has a positive invasion growth rate (Fig. 3a). Hence, in the absence
600 of rock-paper-scissor type cycles, the sign of the invasion growth rates fully

601 determines whether coexistence occurs or not. When the invasion graph, how-
602 ever, has a cycle, one can often use a condition depending on the magnitudes
603 of the invasion growth rates to identify whether the cycle is repelling (Hof-
604 bauer 1981, Schreiber 2000, Patel and Schreiber 2018) and, consequently, the
605 community has a global feasible attractor (Fig. 3a).

606 **3.2.4 Time to Extinction**

607 Even in transient systems where coexistence is not predicted, co-occurrence
608 of species can still take place over ecologically meaningful timescales (Lewon-
609 tin and Cohen 1969, Turelli 1980). Time to extinction provides a quantita-
610 tive measurement of this tendency, with longer time to extinction indicating
611 longer periods of transient coexistence before extinction occurs (Fig. 2g, h).
612 An advantage of this metric is that it can be applied across ecological sys-
613 tems, regardless of its dynamical behaviour – making it especially useful for
614 characterising transient dynamics in which other coexistence metrics do not
615 apply, or in systems where little is known about underlying steady states and
616 attractors.

617 At least in theory, the timing of extinctions resulting from deterministic
618 dynamics can be forecast exactly as a function of observed system states
619 and dynamics. However, most modelling frameworks require additional con-
620 siderations – e.g. in dynamical systems models, abundances approach zero
621 asymptotically, such that they come infinitely close to, but never quite reach,
622 extinction. Common solutions to this problem include including an extinction
623 “cut-off” (quasi-extinction) at an arbitrarily small population size, or include
624 a stochastic component when modelling small populations (Holmes et al.

625 2007). For models where extinctions result from random fluctuations, time
626 to extinction is typically reported in terms of an expected waiting time (i.e.
627 the average time to extinction that might be observed over many repeated tri-
628 als). How, exactly, stochasticity influences time to extinction depends on how
629 randomness is structured at the level of individuals vs. populations (Kendall
630 and Fox 2003) (see Section 4.1.3 for more details).

631 Given relatively simple dynamics and strong theoretical assumptions,
632 mean time to extinction can often be computed using both analytical ap-
633 proximations (Lande and Orzack 1988). For more complex systems, it can
634 often be more efficient to estimate time to extinction directly through long-
635 term simulations of a fitted model (van Nes and Scheffer 2004, Schreiber et al.
636 2023). Simulation-based approaches for studying time to extinction are espe-
637 cially well developed in population ecology, where carefully tuned integrated
638 population models and integral projection models (IPMs) can be applied to
639 accurately forecast population dynamics for well-studied species (Plard et al.
640 2019). Recently, more general methods have been developed that attempt
641 to make similar forecasts using less data and fewer biological assumptions,
642 e.g. based insights from statistical mechanics (Arani et al. 2021) and delay
643 embedding approaches (Clark et al. 2022).

644 **3.3 Quantifying Mechanisms that Promote Coexistence**

645 While our focus is on methods for detecting whether species coexist, a parallel
646 and highly complementary body of work focuses on explaining mechanisms
647 that promote, or alternatively hinder, coexistence in a given community.

648 Broadly, mechanisms that promote coexistence allow species to differentiate
649 among one another in their degree of niche overlap, yielding differences in
650 the strength of intra- and interspecific density dependence (Adler et al. 2018,
651 Chase and Leibold 2009). Coexistence mechanisms can arise in a multitude of
652 ways, such as via trait trade-offs among species (e.g. competition-colonization
653 trade offs; Levins and Culver 1971, Yu and Wilson 2001), specilization of nat-
654 ural enemies and pathogens (e.g. Janzen-Connell hypothesis; Janzen 1970,
655 Connell 1971), differences between species in their limiting resources, or par-
656 titioning of variable environmental conditions—as described below. Many
657 studies seek to understand both the potential for coexistence, as we focus
658 on here, and the underlying mechanisms that allow for coexistence. While
659 an in-depth review of these mechanisms falls outside of our scope, we briefly
660 highlight several of the prominent literature on mechanisms of coexistence.

661 **Resource-Ratio Hypothesis and Limiting Resources** The resource ra-
662 tio hypothesis, commonly referred to as R^* theory, states that, given a single
663 limiting resource, whichever species can persist at the lower resource equi-
664 librium level (e.g. R^*) will outcompete all other species (MacArthur 1972,
665 Tilman 1980, 1982). Extending to multiple resources, n species can coex-
666 ist on n resources within a single site if each species has the lowest R^* for
667 a given resource (and arbitrarily many species can coexist given sufficient
668 spatial heterogeneity), suggesting that niche differences in terms of species'
669 limiting resources can promote species coexistence (Tilman 1982). Since its
670 formalization, the resource-ratio hypothesis has been experimentally tested,
671 with strong support for the theory, although mostly in select grassland and

672 phytoplankton systems due to logistical constraints (reviewed in Miller et al.
673 2005).

674 **Stabilizing and Equalizing Mechanisms** Under a given set of environ-
675 mental conditions, coexistence is promoted when average fitness differences
676 (i.e. equalizing mechanisms) and niche differences (i.e. stabilizing mecha-
677 nisms) are balanced (Chesson 1990a, 2008, Barabás et al. 2018): if niche dif-
678 ferences are small, then coexistence requires that average fitness differences
679 are correspondingly small, otherwise the species with lower fitness will be
680 competitively excluded. Alternatively, when niche differences between species
681 are large, species can coexist even when average fitness differences are large
682 (Adler et al. 2007, Spaak et al. 2023). However, model parameters, such as
683 intra- and inter-specific competition coefficients, contribute to both niche
684 and fitness differences, leading to a complex interdependency between the
685 two mechanisms, and a need to focus on their aggregated, rather than indi-
686 vidual, effects (Song et al. 2019).

687 While the exact formula for determining niche and fitness differences clas-
688 sically depended on the underlying population model and methodological
689 approach (Godoy and Levine 2014, Letten et al. 2017, Spaak et al. 2023),
690 niche differences and fitness differences can be relatively easily quantified
691 for pairs of species, leading to empirical comparisons of mechanisms across
692 species traits (Kraft et al. 2015), phenology (Godoy and Levine 2014), and
693 environmental conditions (Wainwright et al. 2019, Van Dyke et al. 2022).
694 Methods for quantifying these mechanisms have recently been expanded to
695 consider facilitation (Bimler et al. 2018), plant-soil feedbacks (Ke and Wan

696 2020, Kandlikar et al. 2019, 2021, Ke and Wan 2022), and cross-trophic level
697 interactions (Spaak et al. 2021, Song and Spaak 2024), thus extending beyond
698 the traditional focus on within-trophic level competition.

699 **Spatial and Temporal Environmental Variability** Variability in envi-
700 ronmental conditions can increase available niche space, promoting coexis-
701 tence of competing species. This idea dates back decades (MacArthur 1958,
702 Armstrong and McGehee 1980, May and MacArthur 1972, Turelli 1978,
703 Levins 1979), but was formalised into a general mathematical framework
704 by Chesson (1994) for temporal, and (Chesson 2000b) for spatially variable
705 environments. Broadly, environmental variability can promote coexistence,
706 even when fluctuation-independent growth rates may yield competitive ex-
707 clusion, via multiple mechanisms: (*i*) the storage effect, where species par-
708 tition environmental variation, and time periods or locations with beneficial
709 environmental conditions correspond with reduced competition; (*ii*) relative
710 non-linearity, where species each experience their maximum average growth
711 rate at different levels of a fluctuating environmental factor; and (*iii*) growth-
712 density covariance (which only applies for spatial variation), which promotes
713 coexistence if species aggregate in regions where they have high growth rates
714 (Chesson 2000a, 2018, Barabás et al. 2018, Ellner et al. 2019).

715 A recent simulation-based approach allows for alternative formalisation of
716 mechanisms that promote coexistence under variable conditions, in essence
717 by simulating invasion growth rates for each species under scenarios where
718 spatial or temporal structure is disrupted (Ellner et al. 2019). The relative
719 importance and strength of different coexistence mechanisms can then be

720 quantified by comparing invasion rates with and without each structuring
721 aspect (e.g. spatial or temporal heterogeneity), broadly categorizing mech-
722 anisms based on resource availability (Letten et al. 2018), environmental-
723 competitive mechanisms (Hallett et al. 2019, 2023, Aoyama et al. 2022), trait
724 differences (Ellner et al. 2019), top-down and bottom-up forces (Shoemaker
725 et al. 2020), or alternative frameworks.

726 **4 Reconciling Theory and Practice**

727 Recent coexistence research has made great strides in developing effective
728 strategies to bring coexistence theory and practical applications into greater
729 harmony. In the following sections, we first discuss key challenges in integrat-
730 ing coexistence theory with empirical tests (Section 4.1). We then present
731 some general guidelines and a recommended workflow for applying the coex-
732 istence metrics discussed in Section 3.2 to characterise dynamical behaviour
733 in empirical contexts (Section 4.2). Finally, we end with a brief prospectus,
734 in which we outline ongoing challenges in empirical coexistence research, and
735 suggest potential ways forward (Section 4.3).

736 **4.1 Special Challenges in Empirical Systems**

737 Empirical systems are typically highly complex, diverse, and interconnected
738 across space and time. Moreover, ecologists have limited a priori knowledge
739 about the species, environments, and underlying biological processes that
740 structure real world systems. Consequently, in addition to the theoretical
741 caveats and scope limitations associated with each of the metrics discussed

742 above, empirical systems present several general classes of challenges that
743 must be considered regardless of the metric applied. These challenges are
744 discussed in detail below, and include: (4.1.1) the underlying biology of em-
745 pirical systems is often poorly understood; (4.1.2) empirical systems tend to
746 be measured with large sampling uncertainty and (4.1.3) are subject to both
747 demographic and environmental stochasticity; (4.1.4) the spatial and tempo-
748 ral scale of empirical observations are usually highly constrained; and (4.1.5)
749 key ecological properties of empirical systems often violate assumptions that
750 are necessary in analysis of theoretical models.

751 **4.1.1 Incomplete Biological Understanding**

752 There is currently no generally agreed upon “standard model” for describ-
753 ing dynamics in ecological systems. All ecological models must, therefore,
754 be thought of as simplified abstractions, which are at best accurate within a
755 limited scope of times, places, and conditions (MacArthur 1970, Levin 1992).
756 The same caveat is inherited by any coexistence metric applied in empirical
757 contexts: coexistence criteria can be tested for particular theoretical models
758 or mechanisms, but there is no guarantee that these insights can be trans-
759 ferred to any given empirical system. Estimates of time to extinction forecasts
760 illustrate this point particularly well. In a theoretical model, average extinc-
761 tion times can usually be estimated either through analytical formula, or by
762 simulation (Lande et al. 1998, Arani et al. 2021, Schreiber et al. 2023). When
763 applied in practice, however, these forecasts can fail for any number of rea-
764 sons – e.g. because the wrong equations are chosen to represent the system,
765 the model is improperly parameterised, or simply because initial conditions

766 are imperfectly characterised (Auger-Méthé et al. 2016, Plard et al. 2019,
767 Rogers et al. 2022). Moreover, even if model predictions perform well for a
768 particular community and context, there is no guarantee that it will continue
769 to do so for other times, places, and species (Carpenter et al. 2001).

770 Analogous issues exist for all other coexistence metrics. Parameter sen-
771 sitivity analyses, for example, usually focus either on the steady states that
772 are implied by a particular theoretical model (Saavedra et al. 2017), or on
773 local approximations of these states expanded around an observed dynamic
774 trajectory (Cenci and Saavedra 2019). Similarly, although eigenvalue-based
775 estimates of asymptotic stability can be calculated with few assumptions
776 about underlying system dynamics or governing equations (Deyle et al. 2016),
777 these estimates are necessarily only accurate around the specific equilibria
778 under consideration. Thus, changes to the system state (e.g. movement away
779 from a fixed-point equilibrium due to large perturbations) or changes to un-
780 derlying system dynamics (e.g. due to community turnover or environmental
781 variability) will also lead to changes in the corresponding coexistence metrics
782 (Tilman 1982).

783 At least in theory, analyses of invasion growth rates can be generalised
784 across a wider range of system states than is true for other metrics. Neverthe-
785 less, empirical estimates of species invasion rates have been shown to change
786 dramatically across environmental conditions (Matías et al. 2018, Germain
787 et al. 2018, Hallett et al. 2019, Wainwright et al. 2019, Van Dyke et al.
788 2022). Thus, whether or not a species successfully invades when introduced
789 into a community at low abundance might be indicative of its average inva-
790 sion rate, or it could simply be a function of the specific conditions that were

791 tested – potentially overlooking the effects of local vs. regional environmen-
792 tal heterogeneity, inter-annual variability, random chance, etc. While these
793 uncertainties can usually be accounted for in analyses, doing so requires mak-
794 ing strong theoretical assumptions about underlying dynamics and functional
795 forms (Letten et al. 2017, Spaak et al. 2023, Weiss-Lehman et al. 2022).

796 **4.1.2 Observation and Detection Errors**

797 Empirical observations in ecology are notoriously noisy, leading both to high
798 rates of observation error (e.g. differences between true vs. measured species
799 abundances), and detection errors (i.e. failing to detect species or incorrectly
800 classifying species identities). Both of these kinds of error can have major
801 ramifications for studies of coexistence. Most obviously, detection error can
802 bias estimates of time to extinction, asymptotic return rates, and invasion
803 success (Kindsvater et al. 2018, Dornelas et al. 2019). For example, if a species
804 is classified as going extinct even though it is still present in the community,
805 extinction rates and occurrences will be under-estimated – or, alternatively,
806 if surveys fail to detect small populations where extinction times are faster,
807 then extinction estimates will be too high (Kuczynski et al. 2023). Many
808 methods have been developed to help reduce such biases (Shimadzu et al.
809 2016), though again, these tend to require large amounts of data, or strong
810 assumptions about species dynamics and error structure.

811 Even if all species in a community are correctly detected and identified,
812 observation error in abundance estimates can still confound analyses. For
813 example, even small errors in abundance measurements can lead to large bi-
814 ases in model parameters (Bowler et al. 2022), as well as in corresponding

815 estimates of coexistence metrics (Clark and Neuhauser 2018). Particularly
816 strong biases can occur when observation error is large relative to species av-
817 erage abundances. For example, if invasion rates are calculated using ratios,
818 then measurement error can lead to estimates that have no defined mean or
819 variance, which makes them exceedingly difficult to parameterise from em-
820 pirical data (Marsaglia 2006). Similar problems can occur for any kind of
821 ratio distribution where noise is large relative to the quantity being observed
822 – for example, when estimating interaction coefficients based on species’ per-
823 formance in mixture relative to monoculture (Carrara et al. 2015), or even
824 when calculating estimates of species relative abundance or density.

825 **4.1.3 Environmental and Demographic Stochasticity**

826 Thus far, we have focused on deterministic models of species interactions.
827 However, ecological systems often experience extrinsic and intrinsic noise,
828 known as environmental and demographic stochasticity, respectively (Lande
829 et al. 2003, Schreiber 2017). Environmental stochasticity arises from stochas-
830 tic fluctuations in demographic rates due to stochastic fluctuations in envi-
831 ronmental conditions such temperature, precipitation, or nutrient availability.
832 In contrast, demographic stochasticity arises from populations consisting of
833 a finite and discrete number of individuals whose demographic fates are not
834 perfectly correlated – independent coin flips are determining whether each
835 individual survives, grows, or survives.

836 Models with environmental stochasticity share many properties with their
837 deterministic analogs (Levins 1979, Chesson and Ellner 1989, Chesson 1994,
838 Schreiber et al. 2011, Hening and Nguyen 2018, Benaïm and Schreiber 2019).

839 The stochastic analog of a feasible steady states is a feasible statistical equi-
840 librium that describes, in the long-term, the fraction of time spent near
841 any feasible state (Schreiber et al. 2011, Hening and Nguyen 2018, Benaïm
842 and Schreiber 2019). Unlike deterministic models, however, these statistical
843 equilibria are typically stochastic attractors. For example, if environmen-
844 tal stochasticity is added to a Lotka-Volterra model with bistable competi-
845 tors, there is no “unstable” statistical equilibrium that separates exclusion
846 of one species from another. Instead, any feasible initial state may lead to
847 the loss of either species with positive probability (Schreiber 2021, Hening
848 et al. 2022). The stochastic analog of global feasible steady state is known as
849 stochastic persistence. Invasion growth rates are a key metric for identifying
850 whether stochastic persistence occurs or not (Schreiber et al. 2011, Hening
851 and Nguyen 2018, Benaïm and Schreiber 2019). Indeed, the use of invasion
852 growth rates in coexistence theory stemmed from Chesson’s work on the stor-
853 age effect for models accounting for environmental stochasticity (Chesson and
854 Warner 1981, Chesson 1994).

855 For models with environmental stochasticity, extinction typically only
856 occurs asymptotically as population densities approach zero exponentially
857 quickly (Hening and Nguyen 2018, Benaïm and Schreiber 2019). Hence, ex-
858 tinction risk is typically measured by introducing a quasi-extinction threshold
859 below which the species is considered effectively extinct (Fieberg and Ellner
860 2000). In sharp contrast, extinction typically occurs in finite time for models
861 accounting for demographic stochasticity (Schreiber 2017). Hence, coexis-
862 tence is always transient in models with demographic stochasticity. However,
863 these transients may be exceptionally long and well described by mean-field

864 models which average out the effects of demographic stochasticity. In par-
865 ticular, when a mean field model has a feasible local attractor, the time to
866 extinction increases exponentially with community size (Faure and Schreiber
867 2014, Schreiber 2017). Hence, extinction risk can often be safely ignored for
868 sufficiently large populations (Schreiber et al. 2023). In contrast, if the mean
869 field models lacks feasible local attractors, impacts of demographic fluctua-
870 tions mount over time, such that time to extinction can be ecologically rel-
871 evant even for large populations (Faure and Schreiber 2014, Schreiber et al.
872 2023).

873 The simultaneous effects of environmental and demographic stochastic-
874 ity are complex and only beginning to be understood. For example, even if
875 invasion growth rates are positive for the mean field model averaging out
876 the effects of demographic stochasticity, long-runs of unfavorable environ-
877 mental conditions can generate negative transients in the per-capita growth
878 rates of rare species. Under these situations, coexistence times only scale
879 as a power function of community size (Ellner et al. 2020, Prodhomme and
880 Strickler 2021). Hence, even communities with large population sizes may
881 be highly vulnerable to extinction. For these situations, positive invasion
882 growth rates can be a poor metric of coexistence times. For example, Dean
883 and Shnerb (2020) and Pande et al. (2020) showed that increasing envi-
884 ronmental stochasticity can simultaneously make invasion growth rates more
885 positive yet shorten coexistence times; a similar phenomena occurs in models
886 of competing species with Allee effects (Schreiber et al. 2019).

887 4.1.4 The Problem of Scale

888 One of the most pervasive challenges in ecology is that of scale dependence
889 – i.e. that the processes that drive ecological dynamics vary substantially
890 across space, time, and contexts Levin (1992). These cross-scale problems
891 typically manifest in coexistence studies as a result of differences between the
892 scales at which systems are observed and experimentally manipulated, vs. the
893 scales that are most relevant for coexistence (Chesson 2000a). As a simple
894 illustration, consider the random walk model in Fig. 2 (g, h). The relative
895 abundances of species in this model are entirely determined by demographic
896 stochasticity – thus, at the “global” scale (i.e. considering all individuals
897 in the simulation), all but one species will eventually drift to extinction.
898 However, the system can “appear” to be both asymptotically stable and
899 mutually invisable at smaller observational scales due to mass effects (Hubbell
900 2001, Clark et al. 2019) – perturbations that reduce local species abundances
901 below the global average are counteracted by immigration from outside of
902 the local patch, and perturbations that increase local abundances above the
903 global average are counteracted because immigration from outside the patch
904 is slower than within-patch mortality.

905 Similar problems arise for many other kinds of ecological processes and
906 coexistence metrics, though the underlying mechanisms are often more diffi-
907 cult to identify and compensate for (Leibold and Chase 2017). For example,
908 invasion analysis can be challenging to implement using field experiments, as
909 most theoretical frameworks require that invasion rates be averaged across
910 the full range of spatial and temporal variability experienced by the com-

911 munity, whereas most experiments are carried out across a limited range of
912 relatively homogeneous spatial replicates over just a few years. Thus, it can
913 be unclear whether results are indicative of real biological phenomena, or
914 whether they reflect the limited range of conditions that were tested (Kraft
915 et al. 2015). Moreover, these problems cannot be alleviated by simply in-
916 creasing the scale at which observations and experiments are conducted, as
917 observational scales that are too large can also lead to erroneous conclusions
918 about coexistence (Clark et al. 2019). Indeed, it seems likely that different as-
919 pects of coexistence (e.g. for different species, or different temporal periods)
920 are driven by processes that act across many different scales, thereby requir-
921 ing measurements across many different observational scales to accurately
922 capture their effects (MacArthur 1972).

923 Another challenge for temporal scale is the correct estimation of genera-
924 tion times and effective population sizes (N_e). Understanding these param-
925 eters helps in assessing the viability and extinction risk of populations, as
926 they determine the rate of reproduction and genetic diversity, which in turn
927 influence a population's response to disturbances and demographic fluctua-
928 tions (Jonasson et al. 2022). Incorrect estimates of generation times can have
929 major impacts on long-term forecasts – especially in systems that include de-
930 mographically structured population dynamics (Leslie 1966, Brussard et al.
931 1971). Similarly, N_e is particularly important in small or fluctuating popu-
932 lations, where genetic drift and inbreeding can have significant impacts on
933 the long-term persistence of species. Nevertheless, in practice, these impacts
934 are often omitted from models, either due to the technical complexity of in-
935 cluding them, or due to a lack of empirical data or proper genetic markers

936 (Waples and Yokota 2007).

937 **4.1.5 Violations of Theoretical Assumptions**

938 Aspects of real world ecological systems can clash in important ways with
939 common assumptions that are made to simplify theoretical analyses. For ex-
940 ample, many empirical systems lack equilibria (DeAngelis and Waterhouse
941 1987), and some appear to lack any kind of discernible steady state at all
942 (Pimm et al. 2019) – thereby limiting the kinds of coexistence metrics that
943 can be computed. Even in systems that include feasible steady states, com-
944 plex dynamics can impede efforts to approximate system dynamics using sim-
945 ple models. Different community assembly pathways, for example, have been
946 shown to lead to fundamentally different kinds of dynamical behaviour and
947 long-term steady states (Fukami 2015), potentially requiring many different
948 measurements and augmented models to accurately characterise coexistence
949 dynamics (Letten and Stouffer 2019). Moreover, many routine challenges that
950 arise in empirical studies – e.g. transfer shock during invasion experiments,
951 carryover effects from the environment in which young organisms are reared,
952 or even germination failure or high mortality rates – are, in practice, ex-
953 ceedingly difficult to model or quantify without making resulting analyses
954 intractably complicated.

955 An additional challenge is that real world systems are often highly diverse
956 – including anywhere from dozens to thousands of species or taxonomic units
957 even at the smallest possible observational scales (Jurburg et al. 2022). For
958 diversity metrics that rely on measurements of species’ monoculture perfor-
959 mance, pairwise interactions, or invasion growth rates, this high diversity can

960 necessitate impractically large numbers of experimental replicates (but see
961 Song et al. 2022, for a discussion of efficient sampling strategies). In systems
962 that include many feasible local steady states, this problem is magnified,
963 as each of these states might need to be separately assessed as a poten-
964 tial local attractor (Song et al. 2021). And, even when testing for global
965 attractors, high diversity can present a challenge – e.g. even for relatively
966 well-understood classes of dynamical behaviour, building invasion graphs for
967 communities that include more than a few dozen species is technically in-
968 feasible given current algorithms and computational performance (Hofbauer
969 and Schreiber 2022, Spaak and Schreiber 2023).

970 **4.2 Suggested Workflow**

971 Below, we describe a potential workflow for matching available coexistence
972 metrics to different empirical contexts. For each step, we reference a corre-
973 sponding section in this review where more details and relevant citations can
974 be found. Additionally, the general links between dynamical behaviours (Sec-
975 tion 3.1), coexistence metrics (Section 3.2), and empirically relevant research
976 questions and data types are summarised in Fig. 4. Recall that these metrics
977 assess *whether* species can coexist, and additional methods are needed to
978 determine *why* coexistence occurs (Section 3.3).

979 **4.2.1 Select Dynamical Behaviours**

980 The first step is to decide which class of dynamical behaviour (or which com-
981 bination thereof) you wish to focus on. As discussed in Section 3.1, each of

982 these behaviours relates to a distinct definition of coexistence. Existing hy-
983 potheses about the kinds of dynamics that are biologically relevant in your
984 system should be a primary determinant of your choice. For example, if there
985 is reason to believe that your system lacks any discernible feasible steady
986 states, then analyses that focus on transient states may be well-suited. Alter-
987 natively, if dynamics seem to occur in the vicinity of one or more fixed-point
988 equilibria (or well-defined invariant sets), then analyses of feasible steady
989 states or local attractors may offer a good balance between ease of applica-
990 tion and breadth of insight. Finally, if species appear to be able to coexist
991 in the long-term despite large perturbations, but dynamics are highly com-
992 plex and variable – then global attractors may provide the broadest possible
993 insights about coexistence in your system.

994 **4.2.2 Identify Relevant Metrics**

995 The combination of coexistence metrics and analyses that you need to apply
996 will depend on the classes of dynamical behaviours that you want to assess.
997 Section 3.2 includes a detailed discussion of metrics that can be applied for
998 each class of dynamic behaviour. There is a rough hierarchy to these metrics
999 – e.g. time to extinction can be calculated for almost any kind of system,
1000 but provides relatively little information about broader system dynamics,
1001 whereas invasion growth rates can, at least in theory, be used to characterise
1002 the overall global stability of coexistence in a system, but in exchange require
1003 making very strong theoretical assumptions about the processes that govern
1004 system dynamics. This hierarchy does not, however, imply that any one met-
1005 ric is “better” or “more desirable” than the rest – rather, each metric simply

1006 elucidates a different aspect of system behavior, each of which is relevant for
1007 describing different facets of coexistence.

1008 **4.2.3 Assess Available Data and Theory**

1009 Coexistence metrics differ greatly in the kinds of data, theory, and models
1010 that are required to apply them (see details in Section 3.1, and citations to
1011 example applications in Table 4). Thus, it may be necessary to constrain
1012 the classes of dynamical behavior that you choose to study based on the
1013 availability of this information for your system. For example, if you are will-
1014 ing to assume that community dynamics in your system follow the general
1015 Lotka-Volterra equations, then applying most coexistence metrics becomes
1016 relatively simple – e.g. parameter sensitivity and asymptotic return rates
1017 can be computed directly from species interaction coefficients (measured ei-
1018 ther from time-series data, or from pairwise interaction experiments), and
1019 even analysis of global attractors via permanence theory follows a relatively
1020 simple, established protocol.

1021 Alternatively, if theory suggests that interactions in the system are more
1022 complex – e.g. including Allee effects, non-linear growth responses, or even
1023 higher order interactions – then analyses become more complicated, poten-
1024 tially limiting the kinds of behaviour that can be studied, and usually requir-
1025 ing larger quantities and different kinds of data (e.g. from multi-species mix-
1026 tures). For instance, current structural approaches for assessing parameter
1027 sensitivity are generally limited to models that describe species interactions
1028 through a series of linear coefficients – and thus, the approaches cannot yet
1029 be applied in systems dominated by non-linear interactions, as might arise

1030 from “higher-order” interactions, or from some kinds of resource competition
1031 (AlAdwani and Saavedra 2022, Buche et al. 2024). At the far extreme, if
1032 there are no existing models or theories about the kinds of biological pro-
1033 cesses that govern community dynamics in your system, then your analyses
1034 will necessarily be constrained by available data. For these kinds of systems,
1035 flexible data-driven methods such as EDM may be especially useful (see Sec-
1036 tion 3.2.2.1).

1037 **4.2.4 Interpret Your Results**

1038 Finally, recall that empirical systems are not interchangeable with theoret-
1039 ical models. As discussed in Section 4.1, many biologically important aspects
1040 of empirical systems tend not to be implemented in common classes of theo-
1041 retical models (e.g. uncertainty in functional forms of biotic interactions, ob-
1042 servation error, cross-scale processes, etc), and some aspects are so complex
1043 as to preclude tractable model-based representations at all. Consequently,
1044 predictions about coexistence will only ever be as reliable as the assumptions
1045 that are used to produce them. Given great uncertainty, it may be prudent to
1046 apply simpler, less informative coexistence metrics as well as to avoid mak-
1047 ing unfounded theoretical assumptions. Even given solid theoretical backing,
1048 assumptions and underlying models used to assess coexistence should always
1049 be clearly articulated along with other research findings. Additionally, wher-
1050 ever possible, predictions should be tested across multiple different models
1051 or theoretical frameworks, both to ensure the robustness of results, and to
1052 help distinguish among different potential hypotheses about the processes
1053 that are driving community dynamics.

1054 **4.2.5 Rinse and Repeat**

1055 After interpreting your results, you may find that you need to collect more
1056 (or different) kinds of data, plan new experiments, develop alternate theo-
1057 retical models, etc. You may also find that the behaviours and metrics that
1058 you initially chose to focus on are not, in fact, those that are most relevant
1059 (or most readily testable) in your system. We therefore strongly suggest an
1060 iterative approach to studying coexistence – i.e. returning to previous steps
1061 as needed to match your theory, data, and practical needs.

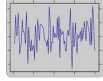
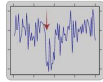

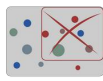
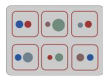
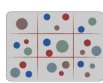
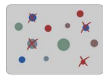
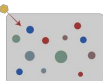
Data type	Metric	Example study descriptions and citations
Time-series observations		
Time series 	Time to extinction	Fit a stochastic dynamical model to observed time-series of algal dynamics to predict average time to extinction for individual species (Clark <i>et al.</i> 2022).
	Parameter sensitivity	Quantified uncertainty in estimates of how strongly species interactions influence community dynamics (Cenci & Saavedra 2018).
	Asymptotic return rate	Used multivariate autoregressive models (MAR) to estimate species interactions and stability properties of naturally varying plankton communities (Ives <i>et al.</i> 2003).
Natural disturbance 	Parameter sensitivity	Tracked transient dynamics of an altered marine ecosystem and its current return path towards benthic fish species domination (Frank <i>et al.</i> 2011).
	Asymptotic return rate	Measured multiple stability parameters, including return rates, from vegetation anomalies in remote sensing data (White <i>et al.</i> 2020).
	Invasion growth rate & Asymptotic return rate	Documented average rate of increase when rare, as well as asymptotic divergence rates across spatial replicates, for grassland plant species following agricultural abandonment, based on a century-long chronosequence (Clark <i>et al.</i> 2019).
Observations of spatial variation		
	Parameter sensitivity	Computed niche and fitness differences across gradients of pollinators and soil conditions using an annual plant population dynamics model (Lanuza <i>et al.</i> 2018).
	Invasion growth rate	Applied a Bayesian modelling approach to estimate invasion criteria for an annual plant community (Bowler <i>et al.</i> 2022).
Experimental manipulations		
Disturbance 	Parameter sensitivity	Fit a resource competition model to observations of two diatom species grown across a temperature gradient. Simulated models with and without temperature fluctuations to test impacts on coexistence (Descamps-Julien & Gonzalez 2005).
	Asymptotic return rate	Documented the recovery of freshwater microbial communities following experimental mixing of a thermally stratified lake (Shade <i>et al.</i> 2012).
Pairwise growth 	Time to extinction	Simulated how third-party species can prolong or shorten competitive outcomes between species pairs (Deng <i>et al.</i> 2022).
	Parameter sensitivity	Used density manipulations to estimate interactions between pairs of annual plants, and used those estimates to predict coexistence in communities with more than two species ("geometric projection") (Buche <i>et al.</i> 2024).
	Asymptotic return rate	Measured algae species and resource concentrations in monoculture to parametrise resource competition models. Analysed model asymptotic stability characteristics to identify local attractors. Model predictions of coexistence were then tested against empirical observations of two-species mixtures (Tilman 1977).
Multispecies growth 	Invasion growth rate	Estimating stabilising niche differences and average fitness differences for a pairwise grassland plant competition experiment using an annual plant competition model, and applied the fitted models to predict competitive outcomes (Kraft <i>et al.</i> 2015).
	Parameter sensitivity	Studied how adding nitrogen and removing leaf pathogens affect the coexistence of species in communities with different numbers of species considering the natural variations in species density and abundance (Granjel <i>et al.</i> 2023).
	Asymptotic return rate & Invasion growth rate	Fit resource competition models based on species characteristics measured in grassland monocultures, and analysed model asymptotic stability and invasion rates to identify local and global attractors. Validated predictions of coexistence against experimentally assembled multi-species mixtures (Clark <i>et al.</i> 2018).
Knock-outs 	Invasion growth rate	Tracked invasion and establishment success of a microbial invader in laboratory microcosms after disturbing (i.e., heat) at different levels (Liu <i>et al.</i> 2012).
	Parameter sensitivity	Removed macroinvertebrate in the sequences in which they are predicted to disappear in response to disturbances and analysed the leaf breakdown rates (Jonsson <i>et al.</i> 2002).
Invasion 	Parameter sensitivity	Removed microbial diversity from soil to create a large diversity gradient and tracked the ability of an invader to grow at each point in the gradient (Mallon <i>et al.</i> 2015).
	Invasion growth rate	A general analytical method that uses both resident community and invader dynamical features to predict whether an invasion causes large long-term impacts on the invaded community (Arnoldi <i>et al.</i> 2022).

Figure 4: Linking data types and analytical methods for quantifying coexistence in empirical contexts. Rows show different data types and the corresponding metrics (Section 3.2) used to assess coexistence in previous studies. Citations show example applications of each approach, with a short discussion of the work.

1062 **4.3 Summary and Outlook**

1063 Above all else, we remind readers that it is vital to define coexistence in terms
1064 of specific dynamical behaviours and metrics. We recommend that studies
1065 specifically state which behaviours and metrics they are applying (e.g. “we
1066 analysed asymptotic return rates to test for the existence of a positive local
1067 attractor”), facilitating comparisons across studies of coexistence. Similarly,
1068 we urge researchers to remain humble and open-minded when interpreting
1069 results from coexistence studies. In practice, there is no such thing as single
1070 metric that is always right – both because metrics can only test for specific
1071 kinds of dynamical behaviour, and because these behaviours describe the-
1072 oretical abstractions of complex empirical systems. To paraphrase the old
1073 adage about models: metrics will always be imperfect, but different metrics
1074 are useful under different circumstances.

1075 Given that multiple, mutually inclusive, behaviours can occur in a given
1076 system, we suggest that future empirical studies of coexistence move away
1077 from single binary tests of whether a particular community can coexist or
1078 not, and instead towards applications of a diverse mixture of coexistence
1079 metrics. Similar shifts in scope away from individual metrics and towards
1080 holistic multidimensional tests have met with much success in general stud-
1081 ies of ecological stability, yielding a complementary mix of different kinds of

1082 qualitative and quantitative understanding (Donohue et al. 2013, Domínguez-
1083 García et al. 2019, Radchuk et al. 2019, Medeiros et al. 2021, Allen-Perkins
1084 et al. 2023). It is likely that the same insights apply to coexistence. For exam-
1085 ple, by quantifying both parameter sensitivity and asymptotic return rates,
1086 studies can account for the effect of perturbations on both rate constants
1087 (e.g. growth rates, interaction coefficients) and state variables (e.g. species
1088 abundances) (Medeiros et al. 2021). Similarly, jointly reporting asymptotic
1089 return rates and invasion growth rates within the same study can help show
1090 how coexistence is likely to respond to large vs. small perturbations (Clark
1091 et al. 2019).

1092 Additionally, we note that a little bit of theory can go a long way – and
1093 making a few targeted theoretical assumptions can greatly reduce the scope
1094 of empirical data needed to test many coexistence hypotheses. For example,
1095 Hallett et al. (2019) used data from rainfall manipulation experiments to
1096 parameterise a demographic model – thereby enabling tests of coexistence
1097 along a global attractor even with limited spatial and temporal replication.
1098 Nevertheless, it is also important to remember that if these *a priori* hypothe-
1099 ses, and corresponding assumptions, are poorly supported, then they can also
1100 lead to misleading conclusions. We therefore recommend explicit considera-
1101 tion of these underlying assumptions, and assessment of the robustness of
1102 results when assumptions are not met. For example, impacts of demographic
1103 stochasticity are often assumed sufficiently small such that they have min-
1104 imal impacts on invasion success in tests of mutual invisibility. To test the
1105 impact of these small effects, Schreiber et al. (2023) reported the probability
1106 of invasion success averaged across a large number of replicates. Similarly,

1107 West and Shnerb (2022) show that even in highly complex systems, average
1108 predictions from a simple comparison of pairwise competition experiments
1109 correlated closely (but not perfectly) with those from more complex coex-
1110 istence criteria. In general, it seems plausible that most classic coexistence
1111 metrics will, on average, produce qualitatively similar results when applied
1112 to empirical data even if all underlying assumptions are not met – so long as
1113 practitioners are careful to acknowledge that these results should be inter-
1114 preted with care.

1115 Lastly, we stress a balance between building on past hypotheses and equa-
1116 tions – which can significantly reduce the data requirements for analyses of
1117 coexistence – and testing alternative hypotheses and corresponding equa-
1118 tions or even behaviours that might better fit the study system. For ex-
1119 ample, many studies of grassland coexistence use identical model structure
1120 (e.g. Levine and HilleRisLambers 2009, Hallett et al. 2019, Kraft et al. 2015,
1121 Van Dyke et al. 2022), facilitating cross study comparison. Simultaneously,
1122 however, Terry and Armitage (2024) has noted that using the same model
1123 structure repeatedly has impeded inferences of coexistence in some empirical
1124 settings, potentially leading to model-specific dependencies of results. To help
1125 avoid this problem, combining insight from across multiple different theoretic-
1126 al frameworks (ideally representing multiple different dynamical behaviours
1127 and metrics) can help test the generality of results, and facilitate analysis
1128 both within and across ecosystems – e.g. by comparing predictions about
1129 coexistence across different sets of theoretical assumptions or environmental
1130 conditions (Ellner et al. 2019, Walker and Gilbert 2023).

1131 **4.3.1 Future Challenges**

1132 We believe that a preeminent challenge for coexistence research in the com-
1133 ing years will be the development of new analytical methods that are built
1134 hand-in-hand with empirical applications. These new methods need not (and
1135 probably should not) seek to define new classes of dynamical behaviour (i.e.
1136 Section 3.1) or even new coexistence metrics (3.2) – however, the current
1137 generation of methods for matching data to metrics and behaviours has been
1138 largely inherited from theoretical studies, and often leave major gaps between
1139 theoretical assumptions and practical applications. In particular, these new
1140 methods should focus on making testable predictions that can be validated
1141 against available data (e.g. “will this species or community persist for the
1142 next X years?”), including long-term observations, controlled field experi-
1143 ments, and the growing body of proxy data coming from genetic, trait, and
1144 remote sensing studies (Borer et al. 2017, Gonzalez et al. 2023). Moreover,
1145 before new methods are introduced to a broader audience, they should be
1146 validated extensively against real world data to make their scope and limi-
1147 tations as clear as possible.

1148 Another important next step in coexistence research will be to compare
1149 relationships between different coexistence metrics and dynamical behaviours
1150 in real world systems. While these relationships are well understood in the-
1151 ory, it is not yet clear how well these theoretical links apply in practice. For
1152 example, insights from studies of ecological stability suggest that multivari-
1153 ate relationships across different metrics are often much more constrained in
1154 empirical systems than is predicted by theory (Donohue et al. 2013, Rad-

1155 chuk et al. 2019). Interestingly, these constrained relationships could greatly
1156 simplify many analyses – e.g. if abundance dynamics for species with very
1157 long predicted time to extinction are, in practice, likely to be associated with
1158 feasible global attractors, then even relatively “simple” metrics could be used
1159 to test for complex dynamical behaviours.

1160 Finally, an enduring challenge for coexistence research is to better match
1161 both the spatial and temporal scales at which empirical data are available to
1162 the scales that are most relevant for coexistence (Chesson 2000a, Clark et al.
1163 2019). Improving this link is critical under ongoing global change, which chal-
1164 lenges many of the assumptions of classic coexistence theory. Strengthening
1165 this link will be important for validating new methods, assessing how well our
1166 mathematical theory translates to empirical predictions, and thus for using
1167 theory to for make predictions that are directly useful for conservation and
1168 restoration applications (HilleRisLambers et al. 2012, Hallett et al. 2023).
1169 Additionally, more general scaling approaches will be critical for identifying
1170 the spatial, temporal, and context-based limits to our ability to understand
1171 and forecast coexistence – e.g. the maximum time horizons across which pre-
1172 dictions about coexistence can be made (Maris et al. 2018, Tredennick et al.
1173 2021).

1174 **4.4 Conclusions**

- 1175 1. ecological coexistence has historically been described using a wide range
1176 of independently developed (and sometimes mutually exclusive) defini-
1177 tions and metrics

- 1178 2. most kinds of community dynamics fall into one of four classes: feasi-
1179 ble steady states, feasible local attractors, feasible global attractors, or
1180 transient states
- 1181 3. these four classes of behaviour can be used to define different aspects
1182 of ecological coexistence, and can be identified and tested using well-
1183 established theoretical metrics: parameter sensitivity (for feasible steady
1184 states), asymptotic return rate (for feasible local attractors), invasion
1185 growth rates (for feasible global attractors), and time to extinction (in
1186 the case of transient states)
- 1187 4. empirical systems present special challenges for studying ecological co-
1188 existence, e.g. due to incomplete biological understanding, impacts of
1189 observation error and stochasticity, the problem of scale, other aspects
1190 of real world systems that violate common theoretical assumptions
- 1191 5. identifying and quantifying ecological coexistence in empirical systems
1192 therefore requires careful consideration of the class of dynamic be-
1193 haviour of interest, the kinds of metrics that can be applied to identify
1194 that behaviour, and the breadth of conclusions that can be drawn given
1195 available data and theoretical understanding
- 1196 6. we stress that there is no single “correct” class of behaviour or metric
1197 for defining and classifying coexistence – we therefore recommend that
1198 future studies take a more holistic approach, e.g. by assessing coexis-
1199 tence across a range of dynamic behaviours and metrics, and carefully
1200 articulating their scope and limitations

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1215 (SJS) proposed the structure for organising different classes of dynamical
1216 behaviours and metrics, with feedback from ATC and LS. All authors con-
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1219 and LS then significantly revised the text to unify concepts, language, and
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1221 include: GB, OG, and SS (parameter sensitivity); ATC and CK (asymptotic
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1223 and environmental and demographic stochasticity); LS (section on quantify-
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