

1 New insights to be gained from a Virtual Ecosystem

2

3 Robert M. EWERS^{1*}, Jacob COOK¹, Olivia Z. DANIEL¹, C. David L. ORME¹, Vivienne GRONER¹, Jaideep
4 JOSHI^{2,3,4,5}, Anna RALLINGS¹, Taran RALLINGS¹, Priyanga AMARASEKARE⁶

5

6 ¹ Georgina Mace Centre for the Living Planet, Imperial College London, Silwood Park Campus,
7 Buckhurst Road, Ascot SL5 7PY, UK

8 ² Advancing Systems Analysis Program, International Institute for Applied Systems Analysis, 2361
9 Laxenburg, Austria

10 ³ Institute of Geography, University of Bern, Hallerstrasse 12, 3012 Bern, Switzerland

11 ⁴ Oeschger Centre for Climate Change Research, University of Bern, Falkenplatz 16, 3012 Bern,
12 Switzerland

13 ⁵ Complexity Science and Evolution Unit, Okinawa Institute of Science and Technology Graduate
14 University, Onna, Okinawa 904-0495, Japan

15 ⁶ Department of Ecology and Evolutionary Biology, University of California Los Angeles, Los Angeles,
16 CA, USA

17

18 * Corresponding author: r.ewers@imperial.ac.uk

19

20 Abstract

21 The myriad interactions among individual plants, animals, microbes and their abiotic environment
22 generate emergent phenomena that will determine the future of life on Earth. Here, we argue that
23 holistic ecosystem models – incorporating key biological domains and feedbacks between biotic and
24 abiotic processes – capable of predicting emergent phenomena are required if we are to
25 understand the functioning of complex, terrestrial ecosystems in a rapidly changing planet. We
26 argue that holistic ecosystem models will provide a framework for integrating the many approaches
27 used to study ecosystems, including biodiversity science, population and community ecology, soil
28 science, biogeochemistry, hydrology and climatology. Holistic models will provide new insights into
29 the nature and importance of feedbacks that cut across scales of space and time, and that connect

30 ecosystem domains such as microbes and animals or above and below ground. They will allow us to
31 critically examine the origins and maintenance of ecosystem stability, resilience and sustainability
32 through the lens of systems theory, and provide a much-needed boost for conservation and the
33 management of natural environments. We outline our approach to developing a holistic ecosystem
34 model – the Virtual Ecosystem – and argue that while the construction of such complex models is
35 obviously ambitious, it is both feasible and necessary.

36

37 [Keywords](#)

38 Ecosystem complexity; Emergent phenomena; General ecosystem model; Organismal physiology;
39 Temperature

40

41 [Introduction](#)

42 Terrestrial ecosystems are complex systems replete with emergent phenomena that challenge our
43 understanding and defy prediction. Part of the problem is a mismatch between the goal of ecology,
44 to understand ecosystems, and the approach of ecologists to that goal, which is largely reductionist.
45 Fifteen years ago, Drew Purves made the bold statement that it's "time to model all life on earth,"
46 (Purves et al. 2013), and went on to lead a team that made a valid claim to having achieved this
47 ground-breaking feat (Harfoot et al. 2014). Yet even this audacious project embedded compromises:
48 it focussed on describing processes at global scales, used a highly representation of plant dynamics,
49 and omitted microbes, and so necessarily did not simulate the local dynamics and cycles of a
50 complete ecosystem. In the decade since these studies were published, the planet has been assailed
51 by global catastrophes of drought, floods, epidemic and unprecedented levels of climate warming.
52 There is an urgent need to develop process-based models that can predict ecosystem responses to
53 these catastrophic phenomena. This is no easy task: ecosystems have been described as "more
54 complex than the space station, and more connected than the internet" (Andrew Young, *pers.*
55 *comm.*). We need models that capture this complexity and connectivity, and rise to the challenge of
56 predicting how ecosystems will fare in a rapidly changing world.

57 Ecosystems arise through the interactions of plants, animals, microbes and the abiotic environment.
58 The actions of individual organisms are driven by their physiology under the dictates of natural
59 selection, and when connected through a web of interactions give rise to a complex system with
60 self-regulating and self-maintaining properties. Describing this complexity through empirical
61 observation is an unrealistic goal, as it would require simultaneous observations of all species, all

62 facets of the abiotic environment, and all biotic interactions. Even if such data were available, they
63 would still be unable to give insight into emergent phenomena arising from non-linear feedbacks
64 and multiple stable states. Simulation using models provides an alternative, and more tractable,
65 route to examining these complex features of complex systems, and hence a better understanding
66 of their consequences.

67 Despite rapid advancements in the construction of detailed ecological models for terrestrial
68 ecosystems (Clark et al. 2011, Harfoot et al. 2014, Fatichi et al. 2019, Geary et al. 2020), these are
69 not yet fully holistic. Our definition of ‘holistic’ encompasses two key aspects: one is the breadth of
70 processes being incorporated, and the other is the diversity of users that might benefit from such
71 models. First, holistic ecosystem models should simultaneously encompass the domains of plants,
72 animals and soil microbes, along with the abiotic drivers that impact those domains (such as
73 temperature, hydrology and soil chemistry). The closest models that currently exist are the “end-to-
74 end” models that have been used to simulate marine environments for several decades (Christensen
75 and Walters 2004, Fulton et al. 2011), and have more recently begun to emerge in freshwater
76 environments (Janssen et al. 2015, Janssen et al. 2019). These models seek to capture the breadth of
77 components and processes that an ecosystem encompasses (Fulton 2010, Geary et al. 2020), but
78 they focus mainly on the biological components of the ecosystems and do not yet allow for
79 feedbacks where the biotic world influences the abiotic. Such feedbacks are common in terrestrial
80 environments (e.g. trees controlling microclimate (Hardwick et al. 2015) and microbes modifying soil
81 chemistry (Philippot et al. 2024)), necessitating their inclusion in holistic ecosystem models for
82 terrestrial environments. The end-to-end models for marine and freshwater environments have
83 demonstrated a broad suite of powerful applications (Plagányi 2007, Geary et al. 2020), and have set
84 a benchmark for terrestrial ecologists to emulate.

85 The second feature of terrestrial holistic ecosystem models is the wide base of users whose
86 demands can be satisfied from a single, unified framework (Box 1). Such models could
87 simultaneously help systems ecologists to examine density- or frequency-dependent feedbacks,
88 disturbance ecologists to predict ecosystem resilience to disturbance, and resource managers to
89 optimise their management plans. They would have extraordinary potential to deliver new insights
90 into the structure, function and emergent properties of natural ecosystems. For example, holistic
91 ecosystem models may present the most viable route to exploring feedbacks across larger temporal
92 and spatial scales and/or across ecosystem domains, and to test hypotheses about the origins of
93 ecosystem stability, resilience and sustainability. These models could supercharge field research by
94 directing attention towards key processes and data gaps, and would be an invaluable tool for guiding
95 the management of natural environments.

96 Inspired by modelling approaches in the marine and freshwater environments, and building on
97 existing knowledge of simple ecosystems and individual ecosystem domains, we are developing a
98 terrestrial Virtual Ecosystem that replicates the many connections among individual organisms and
99 their complex interactions with the abiotic environment. Here, we outline our approach to
100 developing such a holistic ecosystem model, and illustrate the key ecosystem processes being
101 simulated and the ecosystem states being predicted. We argue that such models need to be based
102 on organismal physiology, with an emphasise on environmental temperature as a driving abiotic
103 factor. We argue that holistic ecosystem models can reveal the emergent properties of ecosystems
104 that data alone cannot, and highlight new insights that could emerge. Despite the apparent
105 bewildering level of complexity required to develop such models, we make a positive case for
106 achieving this ambitious goal.

107

108 [The Virtual Ecosystem](#)

109 We are developing a holistic ecosystem model that is designed explicitly to elucidate ecosystem-
110 level emergent phenomena from the perspectives of a wide variety of users and disciplines: the
111 Virtual Ecosystem (Box 1; Virtual Ecosystem Project Team 2024). This model is designed to replicate
112 the basic physiological processes that determine the birth, growth, reproduction and survival of
113 microbes, plants and animals, and the physical processes that determine microclimate and
114 hydrology, which in turn affect, and are affected by, the biotic domains (Figure 1). The Virtual
115 Ecosystem attempts to simultaneously balance the budgets for energy, water, carbon, nitrogen and
116 phosphorus, which will emerge from cycling of matter through plant, animal and microbial
117 functional groups. Organismal physiology, including the dependence of vital rates (e.g. birth, death,
118 metabolism) on temperature and body size (Gillooly et al. 2001, White et al. 2006), drives the biotic
119 domains of the model, with stoichiometry – the balance of carbon, nitrogen and phosphorus within
120 organisms (Sturner and Elser 2002, Agren 2008, Cherif and Loreau 2013) – also playing a central role.
121 There is close coupling between the biotic and abiotic world, and abiotic processes like the
122 movement of heat and water are based on first-principles physics (Maclean and Klings 2021).
123 Finally, we focus on replicating processes across the spatial and temporal scales defined by our set of
124 user stories (Box 1). These mandate a spatial extent encompassing the typical area of natural area
125 management that range from 1 to 40,000 ha (UNEP-WCMC and IUCN 2024), and time scales that run
126 the gamut from short-term management windows (≥ 1 year) to the long-term data series of decades
127 that are needed to adequately detect changes in ecosystem resilience (Boulton et al. 2022).

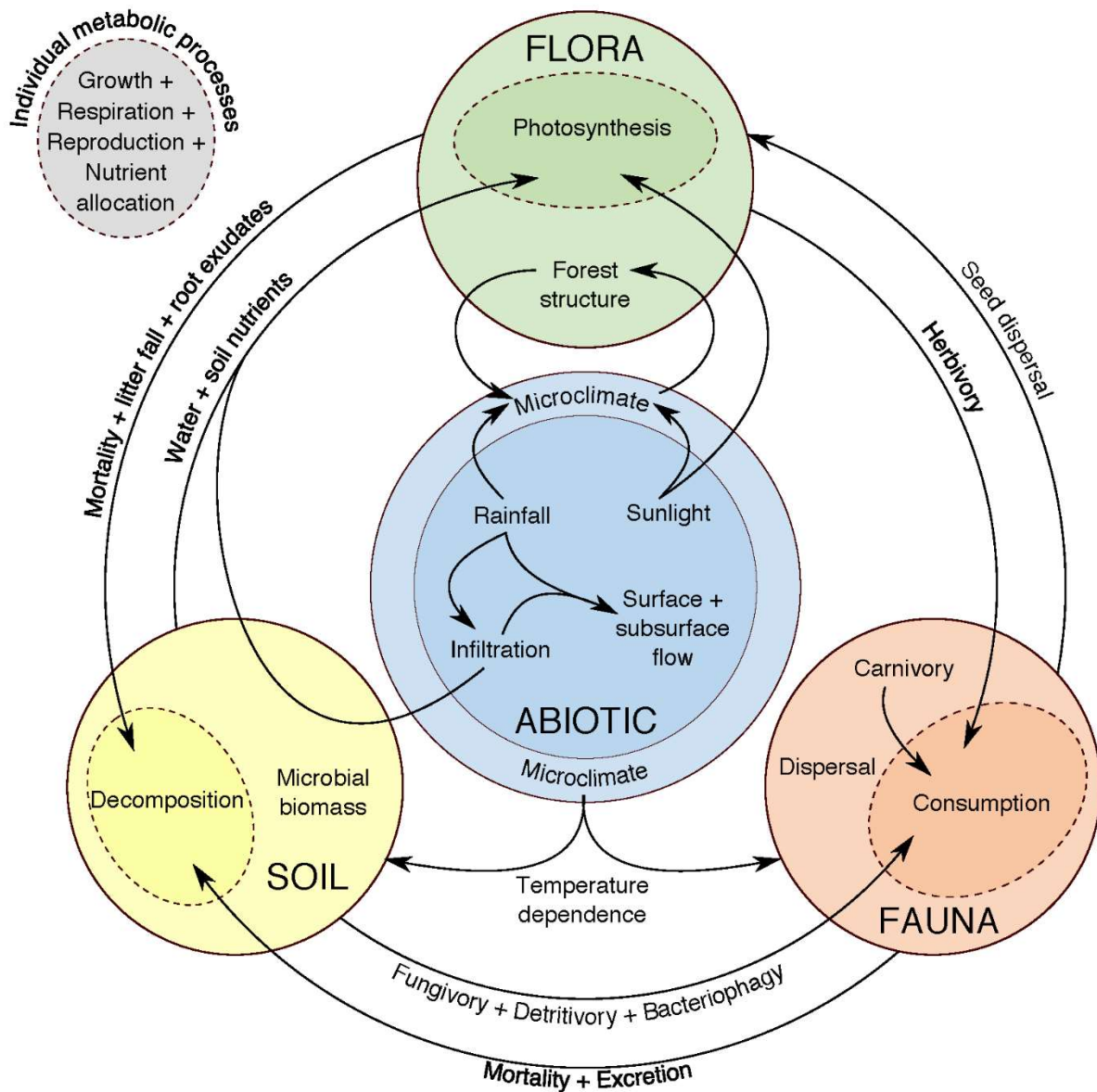
128 We represent the plant, animal and microbe domains as functional groups, as defined by trophic
129 interactions, which provides a tractable means of capturing the myriad species interactions that
130 characterise complex terrestrial ecosystems. We do so because what matters in terms of ecosystem
131 dynamics and the resulting emergent phenomena is not the taxonomic identity of a species, but
132 rather the role it plays in ecosystem dynamics be it a primary producer, a consumer or a
133 decomposer. Use of functional groups rather than individual species is routinely considered a
134 necessary trade-off when integrating biodiversity into complex ecosystem models (Geary et al.
135 2020). Ultimately, it will be computational constraints that limit the diversity of functional groups
136 that can be incorporated into the model, as the number of among-group interactions that need to
137 be replicated increase combinatorially with the number of groups. Where appropriate for a user
138 (Box 1), one or more functional groups can be narrowed down to reflect a target species of interest
139 (Rüger et al. 2020), allowing for species-specific questions to be addressed within the Virtual
140 Ecosystem. Moreover, neutral models can be used to estimate the diversity and abundance
141 distributions of species within functional groups (Fernandes et al. 2022), enabling the Virtual
142 Ecosystem to address biodiversity questions from a species perspective.

143 Our first Virtual Ecosystem model is based on the Stability of Altered Forest Ecosystems (SAFE)
144 Project (Ewers et al. 2011), located in the tropical rainforests of Sabah, Malaysia. Researchers at
145 SAFE have generated open-access data that encompasses large swathes of the ecosystem
146 (<https://zenodo.org/communities/safe>), from the relative abundance and ecosystem energetics of
147 plant (Both et al. 2019, Döbert et al. 2019), animal (Fayle and Ewers 2018, Sharp et al. 2018, Heon et
148 al. 2020, Mitchell et al. 2020) and microbial taxa (Tin et al. 2017, Robinson et al. 2020, Elias 2021), to
149 ecosystem processes (Ewers et al. 2015, Riutta et al. 2019, Mills et al. 2023) and the abiotic
150 environment (Nainar et al. 2012, Hardwick et al. 2018, Riutta et al. 2020, Drewer et al. 2021).

151 Our larger goal is to generalise the Virtual Ecosystem once it is tested and validated with the SAFE
152 data. The basic set of ecosystem processes that drive tropical rainforests are shared in common with
153 other complex ecosystems. The vital biological processes (e.g. growth, survival and reproduction)
154 underly the trophic interactions that form the fundamental building blocks of all communities, the
155 allometries that connect those processes to body size, and abiotic drivers such as temperature and
156 hydrology, are all universally applicable to all terrestrial ecosystems (Fig. 1). Similarly, the basic
157 functional groups in a tropical forest are no different to those of other ecosystems. We define
158 functional groups in terms of trophic interactions (producers, primary consumers and secondary
159 consumers) and shared organismal characteristics based on taxonomy (e.g. plant vs. invertebrate vs.
160 vertebrate), physiology (ectothermic vs. endothermic) and morphology (small vs. large bodied).
161 This equivalence of processes and functional groups ensures the basic structure of the Virtual

162 Ecosystem will apply across other ecosystems in different geographic locations. That basic structure
 163 would need expanding to encompass large environmental differences: by working in a lowland
 164 tropical forest we have no need to simulate processes related to snow, ice and frost tolerance, for
 165 example. For ecosystems whose dynamics are adequately encompassed by the set of processes
 166 modelled in the Virtual Ecosystem, parameterising them with location-specific biotic and abiotic data
 167 should capture the fundamental similarities and differences among different ecosystem types
 168 (Harfoot et al. 2014, Slevin et al. 2015).

169



170

171

172 *Figure 1. The key processes incorporated into the Virtual Ecosystem. The model replicates the*
173 *ecosystem dynamics in four ecological domains, each constructed as a separate module generating*
174 *the dynamics of plants, animals, soil and the abiotic environment respectively. The key metabolic*
175 *processes that operate at the scale of individual organisms – plants, animals and microbes – are*
176 *incorporated into the plant, faunal, and soil modules respectively. Modules will be dynamically*
177 *connected through the transfer of matter and energy.*

178

179 The Virtual Ecosystem implements a map of the key states and processes that both describe and
180 drive complex ecosystems. Our understanding of ecosystem-level connections is an adaptive one,
181 meaning this map is a continuously evolving thought experiment that is routinely updated in
182 response to feedback we receive from colleagues and reviewers, and our own learning as we
183 progress step-by-step through the process of converting the map into code. We use a pattern-
184 oriented modelling approach to ensure we incorporate the minimum number of processes required
185 to adequately replicate the ecosystem-level patterns being investigated (Grimm et al. 2005, Grimm
186 et al. 2017). Currently, we have identified roughly 100 state variables that can be measured and
187 validated, and that are targets for the model to predict. These state variables encompass physical
188 variables like soil temperature and light intensity, and biological variables like canopy height, the
189 abundance of animal functional groups, and the ratio of bacteria to fungi in soil. Because the Virtual
190 Ecosystem is a circular system, each state variable and functional group is both a dependent variable
191 that responds to changes in downstream parameters and functional groups, and also an input for
192 state variables and functional groups connected upstream.

193 The Virtual Ecosystem has approximately 100 processes characterised by that many state variables
194 (representing variables such as the abundance and biomass of functional groups, and resource pools
195 such as the quantity of faeces in the soil), through which water, energy and nutrients are either
196 converted in form or passed from one functional group or resource pool to another. Example
197 processes include denitrification, surface runoff, resource acquisition and animal dispersal. Finally,
198 our thought experiment identifies more than 300 edges connecting the model states to processes.
199 While daunting, this complexity is manageable for two reasons. First, there is a formidable body of
200 knowledge that directly examines the large majority those state variables, processes and their
201 connections, both individually and in combination, giving a theoretical basis to build from. Second,
202 ecologists have discovered some universal, first-principle rules – such as the scaling of vital rates
203 with body size and temperature (Brown et al. 2004) – that allow us to represent this complexity in a
204 tractable way.

205 Our modelling framework has a modular structure that largely aligns with the four key domains of an
206 ecosystem (plants, animals, soil microbes and the abiotic environment; Figure 1) in a spatially and
207 temporally explicit framework. This modular structure allows users to substitute particular modules
208 with alternative formulations geared towards a particular ecosystem of interest, should they wish.
209 We have developed the Virtual Ecosystem using the Python programming environment (Van Rossum
210 and Drake Jr 1995), an open-source software that is freely available and widely used within our
211 anticipated user community, and is well-suited to rapid development and adaptation. We use
212 industry-standard Python coding practices, including enforcing static-type checking ('mypy') and
213 code quality (via 'ruff') using the 'pre-commit' framework. We run comprehensive unit testing using
214 'pytest' to ensure consistent behaviour of code updates. All new code is accepted through peer-
215 reviewed pull requests to the development branch that must pass quality checks. The code is
216 publicly available from GitHub (https://github.com/ImperialCollegeLondon/virtual_ecosystem) to
217 facilitate community engagement with model development.

218

219 -----

220 **Box 1**

221 User stories are a project management tool used to help define what would constitute success for a
222 project. Here, we list eight example user stories of equal importance that would define success for a
223 holistic ecosystem model. For the model to be considered fully successful, the requirements of all
224 user stories would need to be met.

- 225 1. As a systems ecologist, I will be able to identify any core components and sub-networks that
226 exert strong control over the full system dynamics, so that I can understand the mechanisms
227 underlying ecosystem stability.
- 228 2. As a disturbance ecologist, I will be able to track the attenuation of external perturbations
229 through the system, so that I can understand the mechanisms underlying ecosystem
230 resilience.
- 231 3. As a sustainability scientist, I will be able to calculate the rate at which ecosystem services
232 are provided, so that I can make predictions about the long-term sustainability of the
233 ecosystem.
- 234 4. As a biogeochemist, I will be able to track the flow of carbon, nitrogen and phosphorus
235 through the ecosystem, so that I can quantify elemental balances and residence times.
- 236 5. As a hydrologist, I will be able to predict the frequency and magnitude of flood events, so
237 that I can design downstream flood defences.

- 238 6. As a field ecologist, I will be able to identify knowledge gaps that significantly impair our
239 ability to predict ecosystem dynamics, so that I can prioritise future data collection activities.
240 7. As an applied ecologist, I will be able to examine the impact of climate change and extreme
241 climatic events on ecosystem dynamics, so that I can predict the likely future state of the
242 ecosystem.
243 8. As a resource manager, I will be able to predict the outcomes of competing sets of
244 management strategies, so that I can make informed decisions about implementing cost-
245 effective management actions.

246 -----

247

248 First principles, organismal physiology and environmental temperature

249 Our goal is to build a holistic ecosystem model based on first principles: replicating ecological
250 processes to predict empirically observed patterns, and to predict how these patterns may change
251 under ongoing anthropogenic perturbations (e.g. climate change, habitat destruction, and logging).
252 This approach ensures the Virtual Ecosystem is rooted in ecological theory and provides a strong
253 basis for predicting future outcomes under hitherto unobserved environmental conditions (Evans et
254 al. 2012, Connolly et al. 2017). Moreover, a process-based modelling approach can help avoid the
255 potential problems with overfitting that can arise when models are parameterised using empirical
256 data and subsequently validated with the same data (Schuwirth et al. 2019, Dittmer et al. 2023).
257 Overfitting represents an extremely pervasive and difficult problem when dealing with large and
258 complex systems (San Miguel et al. 2012, Dittmer et al. 2023), which terrestrial ecosystems
259 undoubtedly are.

260 We argue that a holistic ecosystem model building from first principles must start with the
261 physiology of individual organisms – the “elementary particles of all ecological systems” (Evans et al.
262 2012). A common set of processes – photosynthesis, respiration and metabolism – underlie all life,
263 and it is these processes that we collectively refer to as “physiology.” The survival, growth and
264 reproduction of any individual organism is ultimately driven by its ability to meet their metabolic,
265 energetic and stoichiometric – i.e. their physiological – needs. These basic physiological processes
266 therefore underpin all trophic (consumer-resource) interactions that take place in the ecosystem
267 and can, in turn, become a dominant cause of mortality. Physiology, then, drives the interactions
268 among organisms and functional groups, which in turn gives rise to population and community
269 dynamics, and ultimately the emergent properties of ecosystems. These basic principles apply
270 regardless of which life domain an organism belongs to.

271 The biochemical processes such as reaction kinetics and enzyme activation that underlie organismal
272 physiology are all temperature-dependent. Endotherms regulate their body temperature to ensure
273 their biochemical process rates are largely decoupled from the environmental temperature in which
274 they exist. But ecosystems are dominated by ectotherms rather than endotherms (Bar-On et al.
275 2018), and the biochemistry and physiology of ectotherms *are* strongly linked to environmental
276 temperature (e.g. Kern et al. 2015). Moreover, endotherms are indirectly affected by temperature
277 due to their interactions with ectothermic resources, mutualists and natural enemies. Temperature,
278 therefore, must also play an integral role in a holistic ecosystem model. The single word
279 “temperature,” however, hides a world of variation. Soil scientists focus on soil temperature, plant
280 ecophysiologicals on leaf temperature, and invertebrate ecologists on ground- or litter-layer air
281 temperature. Moreover, to understand soil microbial respiration rates, what matters is the mean
282 and distribution of soil temperatures (Liu et al. 2018), whereas invertebrate development rates are
283 more commonly linked to cumulative temperatures and degree days (Quinn 2017), and mortality of
284 larger organisms is more likely driven by extreme temperatures (Ratnayake et al. 2019). In the
285 Virtual Ecosystem, then, we have chosen to model microclimate – temperature and humidity – from
286 the top of the canopy to below the ground as part of the holistic ecosystem model, ensuring the
287 model predicts all elements of environmental temperature that matter for organismal physiology.

288

289 [From general ecosystem models to holistic ecosystem models](#)

290 There have been a number of general ecosystem models developed since Odum’s (1957)
291 groundbreaking effort to study the Silver Springs aquatic ecosystem – the first general ecosystem
292 model. A number of general ecosystem models have since been developed (e.g. Fitz et al. 1996,
293 Kimball et al. 1997, McKane et al. 1997, Clein et al. 2000, Childress et al. 2002, Harfoot et al. 2014).
294 There is an even larger set of models have been developed to investigate ecosystem dynamics
295 without claiming to be general ecosystem models (e.g. Dickinson and Henderson-Sellers 1988, Harris
296 et al. 2004, Best et al. 2011, Clark et al. 2011, Fatichi et al. 2012, Maxwell and Condon 2016). The
297 problem, however, is that all of these modelling attempts omit one or more of the key domains of
298 terrestrial ecosystems: plants, animals, microbes and/or the abiotic environment.

299 There are examples of ecosystem models that encompass each of the domains of plants, animals,
300 soil microbes and the abiotic environment. For example, basic physiological principles have been
301 used to replicate patterns of animal biomass and trophic structures (Harfoot et al. 2014), the
302 enzymatic processes that generate soil microbial respiration have been modelled (Sihi et al. 2018,
303 Fatichi et al. 2019), and there are multiple examples of microclimate (Kearney et al. 2014, Maclean

304 and Klinges 2021) and hydrological models (Paniconi and Putti 2015). The most recent crop of
305 general ecosystem models have begun to connect these pieces. These models focus on investigating
306 tree dynamics while incorporating tree physiological, hydrological and biogeochemical processes
307 (e.g. Best et al. 2011, Clark et al. 2011, Fatichi et al. 2012, Fyllas et al. 2014, Christoffersen et al.
308 2016, Maréchaux and Chave 2017, Rödiger et al. 2017), although they still mostly ignore the role of
309 animals (Harfoot et al. 2014) and soil microbes (Crowther et al. 2019). This void exists despite newly
310 emerging evidence that animals may consume as much as half of net primary productivity (Malhi et
311 al. 2022), and that microbes may control rates of soil organic matter turnover (Crowther et al. 2019)
312 and even plant species composition (Yan et al. 2022). Ecosystems are efficient nutrient recyclers and
313 everything that lives must eventually decompose (Wardle 2002). However, even advanced
314 ecosystem simulators routinely gloss over the decomposition half of the dynamics that drive an
315 ecosystem.

316 Encouragingly, progress is being made in connecting those domains, albeit largely in a pairwise
317 fashion. Examples include the use of optimality theory (Prentice et al. 2014) to connect microclimate
318 with plant ecophysiology (Joshi et al. 2022), linking evapotranspiration to hydrological regimes
319 (Sandoval et al. 2023), connecting hydrological and biological dynamics above- and below-ground
320 (Childress et al. 2002), and tying hydrometeorology to the carbon cycle (Paschalis et al. 2015). At the
321 other extreme, heavily simplified ecosystem models have been generated that connect the domains
322 of plant, animal and soil microbes to biogeochemical cycles (Zou et al. 2016, Rizzuto et al. 2024). To
323 date, however, these provide only highly abstracted representations of real-world systems,
324 investigating the connections among domains without considering processes occurring within those
325 domains. If we are to understand the workings of complex ecosystems and predict their future in an
326 ever-changing world, we need realistic depictions of the key biotic interactions and their feedbacks
327 with abiotic drivers.

328 We argue that holistic ecosystem models like the Virtual Ecosystem hold the promise for developing
329 a more universal modelling framework above and beyond that provided by the current generation of
330 general ecosystem models. Such a framework will focus on how physiological processes at the
331 organismal level translate into higher level processes driven by the interactions among organisms
332 and ecosystem domains. It will encompass a broader set of processes within each domain, building
333 on basic physiological processes to connect them with the demographic processes of birth, growth,
334 reproduction and mortality, and the interactions such as predation, competition and mutualism that
335 drive population and community dynamics. The holistic approach will track the movement of matter
336 within and among domains, balancing the budgets for energy, water and carbon, as well as key
337 nutrients such as nitrogen and phosphorus. Moreover, those biogeochemical cycles will be directly

338 connected to the demography of the living organisms that consume, store and process those
339 nutrients. By necessity, this will require the movement of matter among domains, such as the
340 consumption of plants by animals, and the recycling of nutrients through the decomposition of dead
341 organisms in the soil.

342

343 [Novel insights to be gained from holistic ecosystem models](#)

344 [Unifying perspectives and getting the right answer for the right reason](#)

345 The questions that theoretical and applied ecologists ask are as varied as the systems they study.
346 Ecologists are an extraordinarily diverse group of scientists, encompassing biodiversity scientists,
347 population and community ecologists, soil scientists, biogeochemists, hydrologists, climate scientists
348 and everything in between (see Box 1). Members from every corner of this diverse group of
349 researchers could all descend on the same ecosystem at the same time, collect their data and, based
350 on their understanding of their particular domain, generate defensible conclusions about how the
351 system works and what the most important parts of the system are. A whole system understanding
352 needs to unify their answers, and should make it impossible to get the “right” answer for the
353 “wrong” reason. If we can accurately predict population dynamics of key species, for example, but
354 doing so leads to a predicted nitrogen budget that is wildly imbalanced, then our system-level
355 understanding is incomplete. We argue that all of these perspectives on an ecosystem should be
356 reconcilable because they are, after all, describing exactly the same system at exactly the same time.

357 A holistic ecosystem model should encompass the needs of the diverse group of scientists that wish
358 to study a given ecosystem. Each of our different user groups (Box 1) may have different opinions as
359 to what “matters” in an ecosystem, and all of these focal points are important: none are more right
360 or more wrong than any other. What does matter, however, is that ecology delivers a framework
361 that allows these diverse viewpoints on a single system to be reconciled within a common
362 framework. Holistic ecosystem models like the Virtual Ecosystem constitute a key step towards
363 achieving this goal.

364

365 [The role of cross-scale and cross-domain feedbacks](#)

366 Any ecosystem has thousands upon thousands of individual interactions among organisms and their
367 environment operating simultaneously at any given time, and the web of connections among those
368 interactions generates positive and negative feedback loops. Stable ecological systems typically arise
369 when positive feedbacks are dampened (Coyte et al. 2015) and negative feedbacks are strengthened

370 (Landi et al. 2018), but exactly what are the feedbacks in complex ecosystems and how does the
371 balance of negative and positive forces emerge?

372 Feedbacks in complex ecosystems arise from biotic interactions within and between functional
373 groups, which themselves occur within and between domains. Abiotic factors cannot in themselves
374 generate these density- and frequency-dependent feedbacks, but can alter their strength and
375 magnitude. For example, interactions between non-linear feedback loops and environmental
376 variability at the scale of a functional group or domain can lead to the emergence of new
377 phenomena. These new phenomena cannot be predicted solely by the lower scale functional group
378 or domain dynamics in the absence of environmental variability at those lower scales. This is the
379 idea of scale transition (Chesson 2012) that underpins the cross-domain and cross-scale feedbacks
380 that abound in complex ecosystems. Complex ecosystems have myriad, non-linear feedback loops,
381 the net outcome of which determines the overall system dynamics. The advantage of holistic
382 ecosystem models such as Virtual Ecosystem is that the focus on the key biotic interactions and
383 abiotic drivers ensure that these feedbacks arise naturally and are resolved as they transition from
384 one spatial and/or temporal scale to another. As a result, these models can reliably characterize the
385 overall ecosystem dynamics, as well as predict how these dynamics may change under altered
386 environmental conditions.

387 Indeed, examples of cross-scale and cross-domain feedbacks abound. Bacteria operate at temporal
388 and spatial scales that are orders of magnitude smaller than those of elephants, which in turn are
389 orders of magnitude smaller than those of long-lived tropical trees, and yet there are strong,
390 pairwise feedbacks between these domains (Coyte et al. 2015, Beugnon et al. 2021, Li et al. 2022,
391 Ong et al. 2023). Other closely coupled feedbacks occur at very high frequency, such as the
392 connection between photosynthesis in the canopy domain and soil moisture in the soil domain
393 (Joshi et al. 2022). Consumer-resource feedbacks can similarly operate in concert, despite clear
394 biological differences between interacting functional groups. For example, the fractal scaling of body
395 sizes ensures large animals can feed simultaneously with small animals (Holling 1992), causing high
396 frequency resource competition among functional groups whose physiology varies over multiple
397 orders of magnitude in body size. At larger spatial and temporal scales, low level resource flows
398 across habitat compartments can increase the stability of food webs (Huxel and McCann 1998),
399 suggesting functional groups that serve to connect ecosystem domains – such as those that forage
400 both on the ground and in the canopy – might be key determinants of ecosystem stability. Finally,
401 the connections of the nitrogen and phosphorus cycles among the domains of plants, soil and soil
402 microbes are poorly described, yet the fact that those connections exist (Čapek et al. 2018) means
403 the underlying cross-domain feedbacks must also exist.

404 There are often substantial knowledge gaps in how individuals, energy and matter interact across
405 scales and between ecosystem domains, but these have potential to generate powerful feedbacks
406 and emergent phenomena (e.g. Knight et al. 2005, Kamaru et al. 2024). If we are to understand
407 emerging ecological patterns, we have to be able to elucidate the sign and magnitude of cross-scale
408 and cross-domain feedback loops. This is because the characteristic signatures observed at larger
409 scales invariably result from processes acting at smaller scales. For example, root-microbe
410 interactions that operate belowground and at hourly time scales can determine aboveground carbon
411 storage in trees over decadal time scales (Jevon and Lang 2022). The same scale transition is
412 observed when non-random patterns of seedling mortality at ground level on the scale of days and
413 months (Engelbrecht et al. 2007, Comita et al. 2010) might result in seemingly neutral coexistence of
414 adult trees in a forest canopy on the scale of centuries (Hubbell 2001), because density-dependence
415 has already operated on the seedling stage and is no longer apparent when adult trees are studied in
416 isolation. These hidden feedbacks that cross scales and domains can represent powerful forces that
417 determine the structure and dynamics of ecosystems, and models that replicate those processes
418 across similarly diverse scales and domains will be required to gain insight into their actions.

419

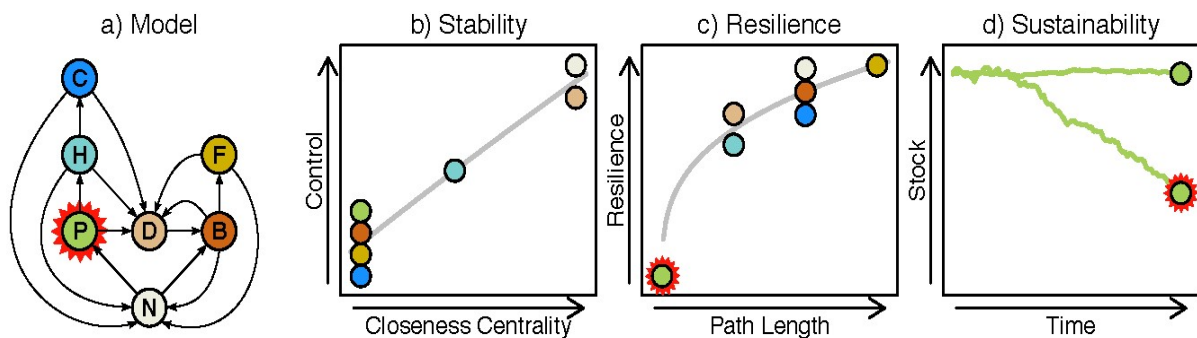
420 [Mechanisms of stability, resilience and sustainability](#)

421 Natural environments generate ecosystem services through the combined actions of millions of
422 interacting individual plants, animals and microbes all growing, respiring and reproducing
423 simultaneously. This web of interactions in turn determines the stability (Tylianakis et al. 2006, Karp
424 et al. 2011), resilience (Karp et al. 2011, Ewers et al. 2015) and sustainability (Fontaine et al. 2005,
425 Wagg et al. 2014) of those ecosystem services. Yet exactly how the physiological processes
426 underlying individual growth, survival and reproduction translate into ecosystem services, and
427 whether this transition can continue to occur unimpeded in a changing world, are questions that
428 defy easy answers (Wagg et al. 2014).

429 Field experiments can reveal the dynamical outcomes of individual ecological processes within a
430 habitat, but experiments to understand emergent system properties are seldom tractable (Fayle et
431 al. 2015). Yet many of the desired traits for ecosystems are emergent phenomena such as stability,
432 resilience and sustainability, all of which arise from the non-linear feedbacks that occur within and
433 between different ecosystem components. Holistic ecosystem models like the Virtual Ecosystem
434 provide a way to integrate behaviour from individual processes into a virtual environment, and
435 thereby provide a more pragmatic tool for exploring what controls the emergent properties of
436 complex ecosystems (Peck 2004). This will open the door for using systems theory to test explicit

437 hypotheses about the origins and maintenance of stability, resilience and sustainability (Figure 2).
 438 For example, systems theory suggests that highly connected actors within complex systems can form
 439 core networks that exert strong control over emergent system properties (Kitano 2002, Mariani et
 440 al. 2019), but are there any such core actors in ecosystems (Fig. 2b)? Moreover, how does this
 441 complex systems concept of core actors relate to ecological concepts such as ecosystem engineers
 442 (Jones et al. 1994), keystone species and keystone communities (Mouquet et al. 2013)? Similarly, do
 443 ecosystems buffer the impact of external perturbations by diffusing their impacts through the many
 444 actors and organisational layers that comprise the system (Mariani et al. 2019), and can this explain
 445 the origin of ecosystem resilience (Suweis et al. 2015) (Fig. 2c)? And finally, to what extent can
 446 ecosystems sustainably deliver ecosystem services in the face of external environmental pressure
 447 (Fig. 2d)? Questions of this nature cannot be answered through the collection of empirical data
 448 alone, or through models that cannot realistically capture the many feedbacks and cross-domain
 449 processes that connect real-world ecosystems. They can, however, be tackled with the tools
 450 provided by holistic ecosystem models.

451



452

453 *Figure 2. Three hypotheses about the emergent properties of rainforest ecosystems that can be*
 454 *tested using holistic ecosystem models. (a) A representation of a simplified ecosystem model adapted*
 455 *from Zou et al. (2016). Circles represent mineral nutrients (N), primary producers (P), herbivores (H),*
 456 *carnivores (C), detritus (D), decomposers (B) and the predators of decomposers (F). Black arrows*
 457 *indicate the flux of nutrients between system components. Red sunburst indicates a direct impact of*
 458 *an environmental perturbation on one component, illustrated here as an impact of climate change*
 459 *on primary producers. (b) Connected components – quantified by metrics such as closeness centrality*
 460 *(Jordán et al. 2007) – exert stronger control over system stability. (c) Components that are more*
 461 *distantly linked – quantified by metrics such as path length (Fath et al. 2019) – to environmental*
 462 *perturbations have increased resilience to that perturbation. (d) Stocks of ecosystem services are*
 463 *sustainable in a steady state system, but become unsustainable in perturbed ecosystems.*

464

465 Better understanding is a prerequisite for better conservation

466 Holistic ecosystem models have the potential to become a powerful tool for managing natural
467 environments. Conservation may often focus on single species or single threats (Geary et al. 2020),
468 but by ignoring the many interactions, feedback loops and dependencies among species and
469 ecosystem domains, the resulting conservation actions can generate perverse ecological outcomes
470 (e.g. Zavaleta et al. 2001, Buckley and Han 2014, Skern-Mauritzen et al. 2016, Geary et al. 2020).
471 Holistic ecosystem models present the opportunity to implement whole ecosystem management
472 through *a priori* adaptive management: running a virtual experiment on a set of feasible
473 management strategies and choosing the most cost-effective one to implement, without waiting for
474 years for field results before improving the existing management plan. Understanding the likely
475 impact of a conservation intervention before committing to that intervention represents a
476 bottleneck in conservation planning that empirical data is struggling to fill (Christie et al. 2020).
477 Moreover, many experiments must run for years or even decades to get the results needed to
478 inform decisions that must be made now (Cusser et al. 2020, Naidu et al. 2022). The fact that they
479 can be experimented on makes a holistic ecosystem model a powerful tool in adaptive management
480 (Geary et al. 2020). Simulation experiments, conducted in the virtual world rather than the real
481 world, can get results faster and cheaper than matching field experiments, and without running into
482 ethical concerns about experimenting with threatened landscapes or species (Crozier and Schulte-
483 Hostedde 2015).

484 *In silico* experiments on system models have been used to great effect in aiding decision making in
485 economics (Burgess et al. 2013) and healthcare (Marshall et al. 2016), including guiding responses to
486 the COVID-19 pandemic (McBryde et al. 2020), and have long been a central component of public
487 and policy discussions around climate change (Steffen et al. 2020). We anticipate similar benefits
488 could be obtained from holistic ecosystem models. Examining model outcomes in response to
489 potential conservation interventions can give insight into the likely effectiveness of those
490 interventions, potentially saving time and money by identifying ineffective actions before
491 implementing them. This approach will also empower adaptative management approaches
492 (Westgate et al. 2013), particularly in time-sensitive situations involving highly threatened
493 ecosystems where we lack time to implement and then learn from a set of conservation actions.
494 Similarly, holistic ecosystem models are more likely to predict how indirect effects might cascade
495 through an ecosystem (Kamaru et al. 2024), helping avoid unintended outcomes from conservation
496 interventions (Zavaleta et al. 2001, Larrosa et al. 2016, Pearson et al. 2022), and thereby preventing
497 the solution to one problem from becoming the origin of another. Finally, models could be used to

498 aid complex management decisions about how to optimise the value of an ecosystem when that
499 ecosystem provides multiple values which might trade-off against each other (Rodríguez et al. 2006).
500 Dynamic simulations using carefully parameterised, holistic ecosystem models provide a viable and
501 tractable tool for predicting the optimal combinations of management actions to guide the
502 behaviour of complex systems such as natural environments towards a desired, future state.

503

504 [History tells us holistic ecosystem models are feasible](#)

505 There is no doubt that constructing a holistic ecosystem model, like the Virtual Ecosystem, is an
506 ambitious goal. But is it feasible? The history of modelling complex systems gives us cause to believe
507 that it is. Across the breadth of the natural sciences, the trajectory has been clear: systems of ever-
508 increasing complexity have been tackled and successfully replicated in computer models, and
509 complex models that were once considered impossible have been successfully constructed. For
510 example, the modelling community that first attempted to construct global digital vegetation models
511 (e.g. Prentice et al. 1992, Neilson and Marks 1994, Foley et al. 1996) endured numerous
512 conversations in which they had to defend the feasibility of their goals (Colin Prentice, *pers. comm.*),
513 and yet these are now a standard component of global climate models (e.g. Drüke et al. 2021, O'ishi
514 et al. 2021). Similarly ambitious attempts have been made to construct the first models of soil
515 microbial systems (Fatichi et al. 2019) and to replicate the basic patterns of animal life at planetary
516 scale (Harfoot et al. 2014). And finally, the class of general ecosystem models that has emerged over
517 the past decade has begun to successfully tie together multiple ecosystem domains, knitting plant
518 ecophysiology with microclimate (Joshi et al. 2022), hydrology (Sandoval et al. 2023),
519 biogeochemistry (Paschalis et al. 2015) and soil microbial processes (Sihi et al. 2018, Fatichi et al.
520 2019). It remains now to tie all of these ecosystem domains together into a single, unified ecosystem
521 model. We see holistic ecosystem models as a logical next step, and the history of pushing the limits
522 of what can be done, and of having succeeded when pushing those limits, gives us confidence that
523 this next step is achievable.

524

525 [Acknowledgements](#)

526 RME, JC, OZD, CDLO, VG, AR and TR are supported by a NOMIS Foundation Distinguished Scientist
527 Award to RME. JJ is supported by the Strategic Initiatives program of the International Institute for
528 Applied Systems Analysis (project RESIST) and the National Member Organizations that support the
529 institute. PA is supported by the U.S. National Science Foundation (DEB-1949796).

531 [References](#)

- 532 Agren, G. I. 2008. Stoichiometry and nutrition of plant growth in natural communities. *Annual*
 533 *Review of Ecology, Evolution and Systematics* **39**:153-170.
- 534 Bar-On, Y. M., R. Phillips, and R. Milo. 2018. The biomass distribution on Earth. *Proceedings of the*
 535 *National Academy of Sciences* **115**:6506-6511.
- 536 Best, M. J., M. Pryor, D. B. Clark, G. G. Rooney, R. L. H. Essery, C. B. Ménard, J. M. Edwards, M. A.
 537 Hendry, A. Porson, N. Gedney, L. M. Mercado, S. Sitch, E. Blyth, O. Boucher, P. M. Cox, C. S.
 538 B. Grimmond, and R. J. Harding. 2011. The Joint UK Land Environment Simulator (JULES),
 539 model description – Part 1: Energy and water fluxes. *Geosci. Model Dev.* **4**:677-699.
- 540 Beugnon, R., J. Du, S. Cesarz, S. D. Jurburg, Z. Pang, B. Singavarapu, T. Wubet, K. Xue, Y. Wang, and N.
 541 Eisenhauer. 2021. Tree diversity and soil chemical properties drive the linkages between soil
 542 microbial community and ecosystem functioning. *ISME Communications* **1**:41.
- 543 Both, S., D. F. R. P. Burslem, T. Riutta, Y. Malhi, N. Majalap, and Y. A. Teh. 2019. Functional traits of
 544 tree species in old-growth and selectively logged forest. Zenodo.
- 545 Boulton, C. A., T. M. Lenton, and N. Boers. 2022. Pronounced loss of Amazon rainforest resilience
 546 since the early 2000s. *Nature Climate Change*.
- 547 Brown, J. H., J. F. Gillooly, A. P. Allen, V. M. Savage, and G. B. West. 2004. Toward a metabolic theory
 548 of ecology. *Ecology* **85**:1771-1789.
- 549 Buckley, Y. M., and Y. Han. 2014. Managing the side effects of invasion control. *Science* **344**:975-976.
- 550 Burgess, S., E. Fernandez-Corugedo, C. Groth, R. Harrison, F. Monti, K. Theodoridis, and M. Waldron.
 551 2013. The Bank of England's forecasting platform: COMPASS, MAPS, EASE and the suite of
 552 models. Bank of England, London, UK.
- 553 Čapek, P., S. Manzoni, E. Kaštovská, B. Wild, K. Diáková, J. Bárta, J. Schneckner, C. Biasi, P. J.
 554 Martikainen, R. J. E. Alves, G. Guggenberger, N. Gentsch, G. Hugelius, J. Palmtag, R. Mikutta,
 555 O. Shibistova, T. Urich, C. Schleper, A. Richter, and H. Šantrůčková. 2018. A plant–microbe
 556 interaction framework explaining nutrient effects on primary production. *Nature Ecology &*
 557 *Evolution* **2**:1588-1596.
- 558 Cherif, M., and M. Loreau. 2013. Plant-herbivore-decomposer stoichiometric mismatches and
 559 nutrient cycling in ecosystems. *Proceedings of the Royal Society B: Biological Sciences*
 560 **280**:20122453.
- 561 Chesson, P. 2012. Scale transition theory: its aims, motivations and predictions. *Ecological*
 562 *Complexity* **10**:52-68.
- 563 Childress, W. M., C. L. Coldren, and T. McLendon. 2002. Applying a complex, general ecosystem
 564 model (EDYS) in large-scale land management. *Ecological Modelling* **153**:97-108.
- 565 Christensen, V., and C. J. Walters. 2004. Ecopath with Ecosim: methods, capabilities and limitations.
 566 *Ecological Modelling* **172**:109-139.
- 567 Christie, A. P., T. Amano, P. A. Martin, S. O. Petrovan, G. E. Shackelford, B. I. Simmons, R. K. Smith, D.
 568 R. Williams, C. F. R. Wordley, and W. J. Sutherland. 2020. Poor availability of context-specific
 569 evidence hampers decision-making in conservation. *Biological Conservation* **248**:108666.
- 570 Christoffersen, B. O., M. Gloor, S. Fauset, N. M. Fyllas, D. R. Galbraith, T. R. Baker, B. Kruijt, L.
 571 Rowland, R. A. Fisher, O. J. Binks, S. Sevanto, C. Xu, S. Jansen, B. Choat, M. Mencuccini, N. G.
 572 McDowell, and P. Meir. 2016. Linking hydraulic traits to tropical forest function in a size-
 573 structured and trait-driven model (TFS v.1-Hydro). *Geosci. Model Dev.* **9**:4227-4255.
- 574 Clark, D. B., L. M. Mercado, S. Sitch, C. D. Jones, N. Gedney, M. J. Best, M. Pryor, G. G. Rooney, R. L.
 575 H. Essery, E. Blyth, O. Boucher, R. J. Harding, C. Huntingford, and P. M. Cox. 2011. The Joint
 576 UK Land Environment Simulator (JULES), model description – Part 2: Carbon fluxes and
 577 vegetation dynamics. *Geosci. Model Dev.* **4**:701-722.
- 578 Clein, J. S., B. L. Kwiatkowski, A. D. McGuire, J. E. Hobbie, E. B. Rastetter, J. M. Melillo, and D. W.
 579 Kicklighter. 2000. Modelling carbon responses of tundra ecosystems to historical and

580 projected climate: a comparison of a plot- and a global-scale ecosystem model to identify
581 process-based uncertainties. *Global Change Biology* **6**:127-140.

582 Comita, L. S., H. C. Muller-Landau, S. Aguilar, and S. P. Hubbell. 2010. Asymmetric density
583 dependence shapes species abundances in a tropical tree community. *Science* **329**:330-332.

584 Connolly, S. R., S. A. Keith, R. K. Colwell, and C. Rahbek. 2017. Process, mechanism, and modeling in
585 macroecology. *Trends in Ecology & Evolution* **32**:835-844.

586 Coyte, K. Z., J. Schluter, and K. R. Foster. 2015. The ecology of the microbiome: Networks,
587 competition, and stability. *Science* **350**:663-666.

588 Crowther, T. W., J. van den Hoogen, J. Wan, M. A. Mayes, A. D. Keiser, L. Mo, C. Averill, and D. S.
589 Maynard. 2019. The global soil community and its influence on biogeochemistry. *Science*
590 **365**:eaav0550.

591 Crozier, G. K. D., and A. I. Schulte-Hostedde. 2015. Towards improving the ethics of ecological
592 research. *Science and Engineering Ethics* **21**:577-594.

593 Cusser, S., C. Bahlai, S. M. Swinton, G. P. Robertson, and N. M. Haddad. 2020. Long-term research
594 avoids spurious and misleading trends in sustainability attributes of no-till. *Global Change*
595 *Biology* **26**:3715-3725.

596 Dickinson, R. E., and A. Henderson-Sellers. 1988. Modelling tropical deforestation: A study of GCM
597 land-surface parametrizations. *Quarterly Journal of the Royal Meteorological Society*
598 **114**:439-462.

599 Dittmer, S., M. Roberts, J. Gilbey, A. Biguri, I. Selby, A. Breger, M. Thorpe, J. R. Weir-McCall, E.
600 Gkrania-Klotsas, A. Korhonen, E. Jefferson, G. Langs, G. Yang, H. Prosch, J. Stanczuk, J. Tang,
601 J. Babar, L. Escudero Sánchez, P. Teare, M. Patel, M. Wassin, M. Holzer, N. Walton, P. Lió, T.
602 Shadbahr, E. Sala, J. Preller, J. H. F. Rudd, J. A. D. Aston, C.-B. Schönlieb, and A.-C.
603 Collaboration. 2023. Navigating the development challenges in creating complex data
604 systems. *Nature Machine Intelligence* **5**:681-686.

605 Döbert, T., B. L. Webber, J. B. Sugau, K. J. M. Dickinson, and R. K. Didham. 2019. Landuse change and
606 species invasion. Zenodo.

607 Drewer, J., M. M. Leduning, R. I. Griffiths, T. Goodall, P. E. Levy, N. Cowan, E. Comynn-Platt, G.
608 Hayman, J. Sentian, N. Majalap, and U. M. Skiba. 2021. Comparison of greenhouse gas fluxes
609 from tropical forests and oil palm plantations on mineral soil. *Biogeosciences* **18**:1559-1575.

610 Drüke, M., W. von Bloh, S. Petri, B. Sakschewski, S. Schaphoff, M. Forkel, W. Huiskamp, G. Feulner,
611 and K. Thonicke. 2021. CM2Mc-LPJmL v1.0: biophysical coupling of a process-based dynamic
612 vegetation model with managed land to a general circulation model. *Geoscientific Model*
613 *Development* **14**:4117-4141.

614 Elias, D. M. O. 2021. Impacts of tropical forest modification on soil microbial communities, function
615 and resilience. Lancaster University, Lancaster, UK.

616 Engelbrecht, B. M. J., L. S. Comita, R. Condit, T. A. Kursar, M. T. Tyree, B. L. Turner, and S. P. Hubbell.
617 2007. Drought sensitivity shapes species distribution patterns in tropical forests. *Nature*
618 **447**:80-82.

619 Evans, M. R., K. J. Norris, and T. G. Benton. 2012. Predictive ecology: systems approaches.
620 *Philosophical Transactions of the Royal Society B: Biological Sciences* **367**:163-169.

621 Ewers, R. M., M. J. W. Boyle, R. A. Gleave, N. S. Plowman, S. Benedick, H. Bernard, T. R. Bishop, E. Y.
622 Bakhtiar, V. K. Chey, A. Y. C. Chung, R. G. Davies, D. P. Edwards, P. Eggleton, T. M. Fayle, S. R.
623 Hardwick, R. Homathevi, R. L. Kitching, M. S. Khoo, S. H. Luke, J. J. March, R. Nilus, M. Pfeifer,
624 S. V. Rao, A. C. Sharp, J. L. Snaddon, N. E. Stork, M. J. Struebig, O. R. Wearn, K. M. Yusah, and
625 E. C. Turner. 2015. Logging cuts the functional importance of invertebrates in tropical
626 rainforest. *Nature Communications* **6**:6836.

627 Ewers, R. M., R. K. Didham, L. Fahrig, G. Ferraz, A. Hector, R. D. Holt, V. Kapos, G. Reynolds, W. Sinun,
628 J. L. Snaddon, and E. C. Turner. 2011. A large-scale forest fragmentation experiment: the
629 Stability of Altered Forest Ecosystems Project. *Philosophical Transactions of the Royal*
630 *Society B* **366**:3292-3302.

631 Fath, B. D., H. Asmus, R. Asmus, D. Baird, S. R. Borrett, V. N. de Jonge, A. Ludovisi, N. Niquil, U. M.
632 Scharler, U. Schückel, and M. Wolff. 2019. Ecological network analysis metrics: the need for
633 an entire ecosystem approach in management and policy. *Ocean & Coastal Management*
634 **174**:1-14.

635 Fatichi, S., V. Y. Ivanov, and E. Caporali. 2012. A mechanistic ecohydrological model to investigate
636 complex interactions in cold and warm water-controlled environments: 1. Theoretical
637 framework and plot-scale analysis. *Journal of Advances in Modeling Earth Systems* **4**.

638 Fatichi, S., S. Manzoni, D. Or, and A. Paschalis. 2019. A mechanistic model of microbially mediated
639 soil biogeochemical processes: a reality check. *Global Biogeochemical Cycles* **33**:620-648.

640 Fayle, T., and R. Ewers. 2018. How does forest conversion and fragmentation affect ant communities
641 and the ecosystem processes that they mediate? Zenodo.

642 Fayle, T. M., E. C. Turner, Y. Basset, R. M. Ewers, G. Reynolds, and V. Novotny. 2015. Whole-
643 ecosystem experimental manipulations of tropical forests. *Trends in Ecology & Evolution*
644 **30**:334-346.

645 Fernandes, L. D., R. E. Hintzen, S. E. D. Thompson, T. Barychka, D. Tittensor, M. Harfoot, T. Newbold,
646 and J. Rosindell. 2022. Species richness and speciation rates for all terrestrial animals
647 emerge from a synthesis of ecological theories. *bioRxiv:2022.2010.2026.513952*.

648 Fitz, H. C., E. B. DeBellevue, R. Costanza, R. Boumans, T. Maxwell, L. Wainger, and F. H. Sklar. 1996.
649 Development of a general ecosystem model for a range of scales and ecosystems. *Ecological*
650 *Modelling* **88**:263-295.

651 Foley, J. A., I. C. Prentice, N. Ramankutty, S. Levis, D. Pollard, S. Sitch, and A. Haxeltine. 1996. An
652 integrated biosphere model of land surface processes, terrestrial carbon balance, and
653 vegetation dynamics. *Global Biogeochemical Cycles* **10**:603-628.

654 Fontaine, C., I. Dajoz, J. Meriguet, and M. Loreau. 2005. Functional diversity of plant–pollinator
655 interaction webs enhances the persistence of plant communities. *PLoS Biology* **4**:e1.

656 Fulton, E. A. 2010. Approaches to end-to-end ecosystem models. *Journal of Marine Systems* **81**:171-
657 183.

658 Fulton, E. A., J. S. Link, I. C. Kaplan, M. Savina-Rolland, P. Johnson, C. Ainsworth, P. Horne, R. Gorton,
659 R. J. Gamble, A. D. M. Smith, and D. C. Smith. 2011. Lessons in modelling and management
660 of marine ecosystems: the Atlantis experience. *Fish and Fisheries* **12**:171-188.

661 Fyllas, N. M., E. Gloor, L. M. Mercado, S. Sitch, C. A. Quesada, T. F. Domingues, D. R. Galbraith, A.
662 Torre-Lezama, E. Vilanova, H. Ramírez-Angulo, N. Higuchi, D. A. Neill, M. Silveira, L. Ferreira,
663 G. A. Aymard C, Y. Malhi, O. L. Phillips, and J. Lloyd. 2014. Analysing Amazonian forest
664 productivity using a new individual and trait-based model (TFS v.1). *Geosci. Model Dev.*
665 **7**:1251-1269.

666 Geary, W. L., M. Bode, T. S. Doherty, E. A. Fulton, D. G. Nimmo, A. I. T. Tulloch, V. J. D. Tulloch, and E.
667 G. Ritchie. 2020. A guide to ecosystem models and their environmental applications. *Nature*
668 *Ecology & Evolution* **4**:1459-1471.

669 Gillooly, J. F., J. H. Brown, G. B. West, V. M. Savage, and E. L. Charnov. 2001. Effects of size and
670 temperature on metabolic rate. *Science* **293**:2248-2251.

671 Grimm, V., D. Ayllón, and S. F. Railsback. 2017. Next-generation individual-based models integrate
672 biodiversity and ecosystems: yes we can, and yes we must. *Ecosystems* **20**:229-236.

673 Grimm, V., E. Revilla, U. Berger, F. Jeltsch, W. M. Mooij, S. F. Railsback, H.-H. Thulke, J. Weiner, T.
674 Wiegand, and D. L. DeAngelis. 2005. Pattern-oriented modeling of agent-based complex
675 systems: lessons from ecology. *Science* **310**:987-991.

676 Hardwick, S., R. Nilus, and R. Ewers. 2018. Forest Microclimate Data From 2nd Order Sites. Zenodo.

677 Hardwick, S. R., R. Toumi, M. Pfeifer, E. C. Turner, R. Nilus, and R. M. Ewers. 2015. The relationship
678 between leaf area index and microclimate in tropical forest and oil palm plantation: forest
679 disturbance drives changes in microclimate. *Agricultural and Forest Meteorology* **201**:187-
680 195.

681 Harfoot, M. B. J., T. Newbold, D. P. Tittensor, S. Emmott, J. Hutton, V. Lyutsarev, M. J. Smith, J. P. W.
682 Scharlemann, and D. W. Purves. 2014. Emergent global patterns of ecosystem structure and
683 function from a mechanistic general ecosystem model. *PLoS Biol* **12**:e1001841.

684 Harris, P. P., C. Huntingford, J. H. C. Gash, M. G. Hodnett, P. M. Cox, Y. Malhi, and A. C. Araújo. 2004.
685 Calibration of a land-surface model using data from primary forest sites in Amazonia.
686 *Theoretical and Applied Climatology* **78**:27-45.

687 Heon, S., P. M. Chapman, O. R. Wearn, H. Berhard, and R. M. Ewers. 2020. Core SAFE project small
688 mammal trapping data. Zenodo.

689 Holling, C. S. 1992. Cross-scale morphology, geometry, and dynamics of ecosystems. *Ecological*
690 *Monographs* **62**:447-502.

691 Hubbell, S. P. 2001. *The Unified Neutral Theory of Biodiversity and Biogeography*. Princeton
692 University Press, Princeton.

693 Huxel, G. R., and K. McCann. 1998. Food web stability: the influence of trophic flows across habitats.
694 *The American Naturalist* **152**:460-469.

695 Janssen, A. B. G., G. B. Arhonditsis, A. Beusen, K. Bolding, L. Bruce, J. Bruggeman, R.-M. Couture, A. S.
696 Downing, J. Alex Elliott, M. A. Frassl, G. Gal, D. J. Gerla, M. R. Hipsey, F. Hu, S. C. Ives, J. H.
697 Janse, E. Jeppesen, K. D. Jöhnk, D. Kneis, X. Kong, J. J. Kuiper, M. K. Lehmann, C. Lemmen, D.
698 Özkundakci, T. Petzoldt, K. Rinke, B. J. Robson, R. Sachse, S. A. Schep, M. Schmid, H.
699 Scholten, S. Teurlincx, D. Trolle, T. A. Troost, A. A. Van Dam, L. P. A. Van Gerven, M.
700 Weijerman, S. A. Wells, and W. M. Mooij. 2015. Exploring, exploiting and evolving diversity
701 of aquatic ecosystem models: a community perspective. *Aquatic Ecology* **49**:513-548.

702 Janssen, A. B. G., S. Teurlincx, A. H. W. Beusen, M. A. J. Huijbregts, J. Rost, A. M. Schipper, L. M. S.
703 Seelen, W. M. Mooij, and J. H. Janse. 2019. PCLake+: A process-based ecological model to
704 assess the trophic state of stratified and non-stratified freshwater lakes worldwide.
705 *Ecological Modelling* **396**:23-32.

706 Jevon, F. V., and A. K. Lang. 2022. Tree biomass allocation differs by mycorrhizal association. *Ecology*
707 **103**:e3688.

708 Jones, C. G., J. H. Lawton, and M. Shachak. 1994. Organisms as ecosystem engineers. *Oikos* **69**:373-
709 386.

710 Jordán, F., Z. Benedek, and J. Podani. 2007. Quantifying positional importance in food webs: A
711 comparison of centrality indices. *Ecological Modelling* **205**:270-275.

712 Joshi, J., B. D. Stocker, F. Hofhansl, S. Zhou, U. Dieckmann, and I. C. Prentice. 2022. Towards a unified
713 theory of plant photosynthesis and hydraulics. *Nature Plants*.

714 Kamaru, D. N., T. M. Palmer, C. Riginos, A. T. Ford, J. Belnap, R. M. Chira, J. M. Githaiga, B. C. Gituku,
715 B. R. Hays, C. M. Kavwele, A. K. Kibungei, C. T. Lamb, N. J. Maiyo, P. D. Milligan, S. Mutisya, C.
716 C. Ng'weno, M. Ogutu, A. G. Pietrek, B. T. Wildt, and J. R. Goheen. 2024. Disruption of an
717 ant-plant mutualism shapes interactions between lions and their primary prey. *Science*
718 **383**:433-438.

719 Karp, D. S., G. Ziv, J. Zook, P. R. Ehrlich, and G. C. Daily. 2011. Resilience and stability in bird guilds
720 across tropical countryside. *Proceedings of the National Academy of Sciences* **108**:21134-
721 21139.

722 Kearney, M. R., A. Shamakhy, R. Tingley, D. J. Karoly, A. A. Hoffmann, P. R. Briggs, and W. P. Porter.
723 2014. Microclimate modelling at macro scales: a test of a general microclimate model
724 integrated with gridded continental-scale soil and weather data. *Methods in Ecology and*
725 *Evolution* **5**:273-286.

726 Kern, P., R. L. Cramp, and C. E. Franklin. 2015. Physiological responses of ectotherms to daily
727 temperature variation. *Journal of Experimental Biology* **218**:3068-3076.

728 Kimball, J. S., M. A. White, and S. W. Running. 1997. BIOME-BGC simulations of stand hydrologic
729 processes for BOREAS. *Journal of Geophysical Research: Atmospheres* **102**:29043-29051.

730 Kitano, H. 2002. Computational systems biology. *Nature* **420**:206-210.

731 Knight, T. M., M. W. McCoy, J. M. Chase, K. A. McCoy, and R. D. Holt. 2005. Trophic cascades across
732 ecosystems. *Nature* **437**:880-883.

733 Landi, P., H. O. Minoarivelo, Å. Brännström, C. Hui, and U. Dieckmann. 2018. Complexity and stability
734 of ecological networks: a review of the theory. *Population Ecology* **60**:319-345.

735 Larrosa, C., L. R. Carrasco, and E. J. Milner-Gulland. 2016. Unintended feedbacks: challenges and
736 opportunities for improving conservation effectiveness. *Conservation Letters* **9**:316-326.

737 Li, G., Y. Jiang, Q. Li, D. An, M. Bao, L. Lang, L. Han, X. Huang, and C. Jiang. 2022. Comparative and
738 functional analyses of fecal microbiome in Asian elephants. *Antonie van Leeuwenhoek*
739 **115**:1187-1202.

740 Liu, Y., N. He, X. Wen, L. Xu, X. Sun, G. Yu, L. Liang, and L. A. Schipper. 2018. The optimum
741 temperature of soil microbial respiration: Patterns and controls. *Soil Biology and*
742 *Biochemistry* **121**:35-42.

743 Maclean, I. M. D., and D. H. Klings. 2021. Microclimc: A mechanistic model of above, below and
744 within-canopy microclimate. *Ecological Modelling* **451**:109567.

745 Malhi, Y., T. Riutta, O. R. Wearn, N. J. Deere, S. L. Mitchell, H. Bernard, N. Majalap, R. Nilus, Z. G.
746 Davies, R. M. Ewers, and M. J. Struebig. 2022. Logged tropical forests have amplified and
747 diverse ecosystem energetics. *Nature* **612**:707-713.

748 Maréchaux, I., and J. Chave. 2017. An individual-based forest model to jointly simulate carbon and
749 tree diversity in Amazonia: description and applications. *Ecological Monographs* **87**:632-664.

750 Mariani, M. S., Z.-M. Ren, J. Bascompte, and C. J. Tessone. 2019. Nestedness in complex networks:
751 Observation, emergence, and implications. *Physics Reports* **813**:1-90.

752 Marshall, D. A., L. Burgos-Liz, K. S. Pasupathy, W. V. Padula, M. J. Ijzerman, P. K. Wong, M. K. Higashi,
753 J. Engbers, S. Wiebe, W. Crown, and N. D. Osgood. 2016. Transforming healthcare delivery:
754 integrating dynamic simulation modelling and big data in health economics and outcomes
755 research. *PharmacoEconomics* **34**:115-126.

756 Maxwell, R. M., and L. E. Condon. 2016. Connections between groundwater flow and transpiration
757 partitioning. *Science* **353**:377-380.

758 McBryde, E. S., M. T. Meehan, O. A. Adegboye, A. I. Adekunle, J. M. Caldwell, A. Pak, D. P. Rojas, B.
759 M. Williams, and J. M. Trauer. 2020. Role of modelling in COVID-19 policy development.
760 *Paediatric Respiratory Reviews* **35**:57-60.

761 McKane, R. B., E. B. Rastetter, G. R. Shaver, K. J. Nadelhoffer, A. E. Giblin, J. A. Laundre, and F. S.
762 Chapin III. 1997. Reconstruction and analysis of historical changes in carbon storage in arctic
763 tundra. *Ecology* **78**:1188-1198.

764 Mills, M. B., Y. Malhi, R. M. Ewers, L. K. Kho, Y. A. Teh, S. Both, D. F. R. P. Burslem, N. Majalap, R.
765 Nilus, W. Huaraca Huasco, R. Cruz, M. M. Pillco, E. C. Turner, G. Reynolds, and T. Riutta.
766 2023. Tropical forests post-logging are a persistent net carbon source to the atmosphere.
767 *Proceedings of the National Academy of Sciences* **120**:e2214462120.

768 Mitchell, S. L., J. E. Bicknell, D. P. Edwards, N. J. Deere, H. Bernard, Z. G. Davies, and M. J. Struebig.
769 2020. Spatial replication and habitat context matters for assessments of tropical biodiversity
770 using acoustic indices. *Ecological Indicators* **119**:106717.

771 Mouquet, N., D. Gravel, F. Massol, and V. Calcagno. 2013. Extending the concept of keystone species
772 to communities and ecosystems. *Ecology Letters* **16**:1-8.

773 Naidu, D. G. T., S. Roy, and S. Bagchi. 2022. Loss of grazing by large mammalian herbivores can
774 destabilize the soil carbon pool. *Proceedings of the National Academy of Sciences*
775 **119**:e2211317119.

776 Nainar, A., R. P. D. Walsh, K. Bidin, and K. V. Annammala. 2012. The hydrology component of the
777 Stability of Altered Forest Ecosystems (SAFE) Project - experimental design and preliminary
778 nutrient data. Pages 1535-1541 *in* UMT 11th International Annual Symposium on
779 Sustainability Science and Management, Terengganu, Malaysia.

780 Neilson, R. P., and D. Marks. 1994. A global perspective of regional vegetation and hydrologic
781 sensitivities from climatic change. *Journal of Vegetation Science* **5**:715-730.

782 O'ishi, R., W.-L. Chan, A. Abe-Ouchi, S. Sherriff-Tadano, R. Ohgaito, and M. Yoshimori. 2021.
783 PMIP4/CMIP6 last interglacial simulations using three different versions of MIROC:
784 importance of vegetation. *Climate of the Past* **17**:21-36.

785 Odum, H. T. 1957. Trophic structure and productivity of Silver Springs, Florida. *Ecological*
786 *Monographs* **27**:55-112.

787 Ong, L., W. H. Tan, L. C. Davenport, K. R. McConkey, M. K. A. b. Mat Amin, A. Campos-Arceiz, and J.
788 W. Terborgh. 2023. Asian elephants as ecological filters in Sundaic forests. *Frontiers in*
789 *Forests and Global Change* **6**.

790 Paniconi, C., and M. Putti. 2015. Physically based modeling in catchment hydrology at 50: Survey and
791 outlook. *Water Resources Research* **51**:7090-7129.

792 Paschalis, A., S. Fatichi, G. G. Katul, and V. Y. Ivanov. 2015. Cross-scale impact of climate temporal
793 variability on ecosystem water and carbon fluxes. *Journal of Geophysical Research:*
794 *Biogeosciences* **120**:1716-1740.

795 Pearson, D. E., T. J. Clark, and P. G. Hahn. 2022. Evaluating unintended consequences of intentional
796 species introductions and eradications for improved conservation management.
797 *Conservation Biology* **36**:e13734.

798 Peck, S. L. 2004. Simulation as experiment: a philosophical reassessment for biological modeling.
799 *Trends in Ecology & Evolution* **19**:530-534.

800 Philippot, L., C. Chenu, A. Kappler, M. C. Rillig, and N. Fierer. 2024. The interplay between microbial
801 communities and soil properties. *Nature Reviews Microbiology* **22**:226-239.

802 Plagányi, É. E. 2007. Models for an ecosystem approach to fisheries. FAO, Rome.

803 Prentice, I. C., W. Cramer, S. P. Harrison, R. Leemans, R. A. Monserud, and A. M. Solomon. 1992. A
804 global biome model based on plant physiology and dominance, soil properties and climate.
805 *Journal of Biogeography* **19**:117-134.

806 Prentice, I. C., N. Dong, S. M. Gleason, V. Maire, and I. J. Wright. 2014. Balancing the costs of carbon
807 gain and water transport: testing a new theoretical framework for plant functional ecology.
808 *Ecology Letters* **17**:82-91.

809 Purves, D., J. P. W. Scharlemann, M. Harfoot, T. Newbold, D. P. Tittensor, J. Hutton, and S. Emmott.
810 2013. Time to model all life on Earth. *Nature* **493**:295-297.

811 Quinn, B. K. 2017. A critical review of the use and performance of different function types for
812 modeling temperature-dependent development of arthropod larvae. *Journal of Thermal*
813 *Biology* **63**:65-77.

814 Ratnayake, H. U., M. R. Kearney, P. Govekar, D. Karoly, and J. A. Welbergen. 2019. Forecasting
815 wildlife die-offs from extreme heat events. *Animal Conservation* **22**:386-395.

816 Riutta, T., R. M. Ewers, Y. Malhi, and N. Majalap. 2019. Changing carbon dioxide and water budgets
817 from deforestation and habitat modification. Zenodo.

818 Riutta, T., Y. Malhi, R. M. Ewers, and N. Majalap. 2020. Microclimate at SAFE Flux Tower. Zenodo.

819 Rizzuto, M., S. J. Leroux, and O. J. Schmitz. 2024. Rewiring the Carbon cycle: a theoretical framework
820 for animal-driven ecosystem carbon sequestration. *Journal of Geophysical Research:*
821 *Biogeosciences* **129**:e2024JG008026.

822 Robinson, S. J. B., D. Elias, D. Johnson, S. Both, T. Riutta, T. Goodall, N. Majalap, N. P. McNamara, R.
823 Griffiths, and N. Ostle. 2020. Soil fungal community characteristics and mycelial production
824 across a disturbance gradient in lowland dipterocarp rainforest in Borneo. *Frontiers in*
825 *Forests and Global Change* **3**.

826 Rödig, E., A. Huth, F. Bohn, C. Rebmann, and M. Cuntz. 2017. Estimating the carbon fluxes of forests
827 with an individual-based forest model. *Forest Ecosystems* **4**:4.

828 Rodríguez, J. P., T. D. Beard, E. M. Bennett, G. S. Cumming, S. J. Cork, J. Agard, A. P. Dobson, and G.
829 D. Peterson. 2006. Trade-offs across space, time, and ecosystem services. *Ecology and*
830 *Society* **11**.

831 Rüger, N., R. Condit, D. H. Dent, S. J. DeWalt, S. P. Hubbell, J. W. Lichstein, O. R. Lopez, C. Wirth, and
832 C. E. Farris. 2020. Demographic trade-offs predict tropical forest dynamics. *Science*
833 **368**:165-168.

834 San Miguel, M., J. H. Johnson, J. Kertesz, K. Kaski, A. Díaz-Guilera, R. S. MacKay, V. Loreto, P. Érdi, and
835 D. Helbing. 2012. Challenges in complex systems science. *The European Physical Journal*
836 *Special Topics* **214**:245-271.

837 Sandoval, D., I. C. Prentice, and R. L. B. Nóbrega. 2023. Simple process-led algorithms for simulating
838 habitats (SPLASH v.2.0): calibration-free calculations of water and energy fluxes. *EGUsphere*
839 **2023**:1-118.

840 Schuwirth, N., F. Borgwardt, S. Domisch, M. Friedrichs, M. Kattwinkel, D. Kneis, M. Kuemmerlen, S.
841 D. Langhans, J. Martínez-López, and P. Vermeiren. 2019. How to make ecological models
842 useful for environmental management. *Ecological Modelling* **411**:108784.

843 Sharp, A., M. Barclay, A. Chung, and R. Ewers. 2018. Beetle Diversity. Zenodo.

844 Sihi, D., E. A. Davidson, M. Chen, K. E. Savage, A. D. Richardson, T. F. Keenan, and D. Y. Hollinger.
845 2018. Merging a mechanistic enzymatic model of soil heterotrophic respiration into an
846 ecosystem model in two AmeriFlux sites of northeastern USA. *Agricultural and Forest*
847 *Meteorology* **252**:155-166.

848 Skern-Mauritzen, M., G. Ottersen, N. O. Handegard, G. Huse, G. E. Dingsør, N. C. Stenseth, and O. S.
849 Kjesbu. 2016. Ecosystem processes are rarely included in tactical fisheries management. *Fish*
850 *and Fisheries* **17**:165-175.

851 Slevin, D., S. F. B. Tett, and M. Williams. 2015. Multi-site evaluation of the JULES land surface model
852 using global and local data. *Geosci. Model Dev.* **8**:295-316.

853 Steffen, W., K. Richardson, J. Rockström, H. J. Schellnhuber, O. P. Dube, S. Dutreuil, T. M. Lenton, and
854 J. Lubchenco. 2020. The emergence and evolution of Earth System Science. *Nature Reviews*
855 *Earth & Environment* **1**:54-63.

856 Sterner, R. W., and J. J. Elser. 2002. *Ecological Stoichiometry: The Biology of Elements from*
857 *molecules to the Biosphere*. Princeton University Press, Princeton.

858 Suweis, S., J. Grilli, J. R. Banavar, S. Allesina, and A. Maritan. 2015. Effect of localization on the
859 stability of mutualistic ecological networks. *Nature Communications* **6**:10179.

860 Tin, H. S., K. Palaniveloo, J. Anilik, M. Vickneswaran, Y. Tashiro, C. S. Vairappan, and K. Sakai. 2017.
861 Impact of land-use change on vertical soil bacterial communities in Sabah. *Microbial Ecology*
862 **75**:459–467.

863 Tylianakis, J. M., T. Tscharntke, and A.-M. Klein. 2006. Diversity, ecosystem function, and stability of
864 parasitoid-host interactions across a tropical habitat gradient. *Ecology* **87**:3047-3057.

865 UNEP-WCMC, and IUCN. 2024. *Protected Planet: The World Database on Protected Areas (WDPA)*.
866 UNEP-WCMC and IUCN, Cambridge, UK.

867 Van Rossum, G., and F. L. Drake Jr. 1995. *Python reference manual*. Centrum voor Wiskunde en
868 Informatica Amsterdam, Amsterdam, The Netherlands.

869 Virtual Ecosystem Project Team. 2024. *Welcome to the Virtual Ecosystem*.

870 Wagg, C., S. F. Bender, F. Widmer, and M. G. A. van der Heijden. 2014. Soil biodiversity and soil
871 community composition determine ecosystem multifunctionality. *Proceedings of the*
872 *National Academy of Sciences* **111**:5266-5270.

873 Wardle, D. A. 2002. *Communities and Ecosystems: Linking the Aboveground and Belowground*
874 *Components*. Princeton University Press, Princeton, USA.

875 Westgate, M. J., G. E. Likens, and D. B. Lindenmayer. 2013. Adaptive management of biological
876 systems: a review. *Biological Conservation* **158**:128-139.

877 White, C. R., N. F. Phillips, and R. S. Seymour. 2006. The scaling and temperature dependence of
878 vertebrate metabolism. *Biology Letters* **2**:125-127.

879 Yan, X., J. M. Levine, and G. S. Kandlikar. 2022. A quantitative synthesis of soil microbial effects on
880 plant species coexistence. *Proceedings of the National Academy of Sciences*
881 **119**:e2122088119.

- 882 Zavaleta, E. S., R. J. Hobbs, and H. A. Mooney. 2001. Viewing invasive species removal in a whole-
883 ecosystem context. *Trends in Ecology & Evolution* **16**:454-459.
- 884 Zou, K. J., E. Thebault, G. Lacroix, and S. Barot. 2016. Interactions between the green and brown food
885 web determine ecosystem functioning. *Functional Ecology* **30**:1454-1465.
- 886