- ecophylo: Simulating and assessing eco-evolutionary dynamics
- under past environmental changes in Python and R
- ⁴ Elizabeth Barthelemy^{1*}, Maxime Jaunatre¹, and Francois Munoz¹
- ¹ Université Grenoble Alpes, LIPhy, 140 Rue de la Physique, 38402 Saint-Martin-d'Hères, France
- 6 Running title: ecophylo: simulating eco-evolutionary dynamics
- 7 Research article
- 8 Word count: XXXXX
- (*) Corresponding author, elizabeth.barthelemy@univ-grenoble-alpes.fr

Abstract

15

16

17

18

19

20

21

22

24

27

- We introduce the Python package ecophylo dedicated to coalescent-based simulation of eco-evolutionary dynamics. Species assemblages and their shared ancestry can be simulated by jointly taking into account 12 the influence of past demographic fluctuations and extinctions along with how divergent genotypes have introduced new species over time through speciation. 14
 - The shared co-ancestry of present individuals is simulated backward in time using coalescent theory. Speciation events are then sprinkled over the simulated genealogy conditionally to its topology and branch lengths. The phylogenetic relationships amongst individuals and their abundances are finally obtained by merging paraphyletic clades into single species. Coalescent reconstruction of the genealogy of individuals can be simulated to represent past demographic fluctuations due to varying habitat availability, or include multiple communities linked by migration events.
- The package includes tools to simulate large numbers of datasets and associated summary statistics, so that Approximate Bayesian Computation methods can be used to estimate parameter values for these processes. Diverse patterns of taxonomic and phylogenetic compositions can be generated. The 23 first version of the package allows simulating neutral coalescent genealogies, and will incorporate further non-neutral eco-evolutionary scenarios in future. The package can be used to explore how past demographic fluctuations have affected species abundances and phylogenetic relationships, and to estimate the parameters of these processes based on observed patterns. We provide step by step examples in both Python and R languages.
- Key-words: eco-evolutionary modelling; community phylogeny; coalescent; demographic stochasticity, ecological drift, extinction-speciation dynamics

Introduction

Observed species distributions and biodiversity patterns are shaped by current ecological processes but also reflect the influence of past evolutionary and biogeographic dynamics (Svenning 2015). For instance, alternating periods of contraction and expansion of suitable environmental conditions should affect both demographic (Avise 2009) and diversification dynamics over time (Barthelemy et al. 2021, Lewitus and Morlon 2018). Hence, a fundamental goal of biogeography is to understand how changes in suitable environmental conditions due to past climatic and geomorphologic history have shaped biodiversity patterns observed at present (Bennett 1990). Historical biogeography typically investigates how species appear, go extinct and migrate, without considering the role of demography and community assembly dynamics over time (e.g., Yu, Harris & He, 2010). Conversely, population genetics and phylogeography emphasize the joint role of migration, mutation and drift in driving patterns of population genetic diversity in space and time (Avise, 2009). Comparative phylogeographic approaches aim to grasp congruent or differing influence of past historical events led by environmental fluctuations on several co-occurring taxa (Arbogast and Kenagy 2001, Swenson 2019, Overcast et al. 2019, 2020). Concurrently, the neutral theory of biogeography has underlined the role of migration, speciation and drift in shaping patterns of taxonomic diversity in space and time (Hubbell, 2001). Integrative modeling approaches are still needed to bridge the gap between phylogeography and biogeography, in order to better understand biodiversity dynamics at multiple spatial and temporal scales and their imprint in extant biodiversity patterns (Lexer et al 2013).

Furthermore, most approaches investigating how intertwined ecological and evolutive forces shape the relative abundances of species have assumed an equilibrium state of biodiversity with present habitat availability and configuration. However, the current state of biodiversity can retain the influence of past environmental conditions (Svenning and Skov 2005, Ordonez and Svenning 2016). The neutral theory of biodiversity

and configuration. However, the current state of biodiversity can retain the influence of past environmental conditions (Svenning and Skov 2005, Ordonez and Svenning 2016). The neutral theory of biodiversity (Hubbell 2001) assumes constancy of metacommunity size Jm to predict the composition of regional biota under a speciation-drift equilibrium, estimated model applied in various biomes across the globe (Jabot and Chave 2008, Etienne et al. 2006). However, past environmental variations (especially climate) should have made habitat properties and species numbers in regional biota to fluctuate over time, i.e., Jm is not constant for a given biome. In the case where these fluctuations occur rapidly compared to the expected time-to-equilibrium of speciation, migration and drift dynamics (for instance with long-lived organisms with slow population dynamics), we expect that current biodiversity patterns should retain the signature of past environmental fluctuations. Thus by allowing J_m to vary at specific ages of the past we can relax this consistency assumption and account for the discordance of demographic histories between distinct regional species pools. Such variation has been considered in phylogeographic models of genetic diversity with changing population size, but seldom in multispecies biogeographic models of biodiversity dynamics (Barthelemy et al. 2021).

Over long time scales, major geological events have affected diversification rates, ie. the outcome of extinction and speciation, leading to increased phylogenetic diversity (Alroy 2008). The separation of the geographical range of multi-species assemblages through the development of physical barriers can lead to allopatric speciation - a process well known to biogeographers as vicariance. Also, the ability of species to cross biogeographic borders and migrate to a given region can increase the phylogenetic diversity of the regional pool (Pennington 2004). Dispersal and vicariance are thus often considered as competing hypothesis used to

explain the spatial distributions of extant taxa. Hence, past environmental fluctuations and biogeographic events of vicariance and/or migration have jointly influenced the evolutionary trajectory of multi-species assemblages. Here we propose a novel simulation-based approach in which we consider how assembly dynamics in temporally changing environments (ecological perspective) affect speciation and extinction dynamics over a long-term (evolutionary perspective), depending on environmental changes over time. Here, we introduce a new Python library dedicated to the simulation of multispecies eco-evolutionary dynamics. We expose the logic and advantages of the approach to examine how past multi-species non-equilibrium dynamics have shaped patterns of taxonomic and phylogenetic diversity. We show how the library can be used to design in silico experiments (Zurell 2010) to address the possible outcome of (meta)community models. Simulating ecological communities and the phylogenetic diversity within and between assemblages according to different scenarios can help establish a benchmark against which to infer the signatures of community-wide past biogeographic processes from the resulting patterns of taxonomic and phylogenetic diversity. The package includes options to simulate large numbers of datasets over broad ranges of parameters and scenarios of past demographic events and fluctuations. These methods are destined to be used alongside ABC methods, so as to estimate parameters of past demographic fluctuation from the observation of actual patterns of diversity (Csillery et al 2015).

87 Core simulation algorithm in ecophylo.simulate

88 Coalescent-based simulation of assemblage genealogies

The core model rests on the fundamental hypothesis that stochastic population dynamics rule the patterns of relative species abundances in a given habitat over time, depending on the regional habitat extant henceforth denoted J_m (Hubbell, 2001). Following the Hudson coalescent model (Hudson 1983), we assume that all individuals shrunk to their haplotypes in a multi-species assemblage can reproduce freely (panmixia assumption), with equal fitness (neutral assumption). The dynamics of the assemblage can be traced through the structure of their genealogy, i.e. by tracing the shared co-ancestry of extant individuals backwards in time until a single common ancestor is found (Kingman 1982). Coalescence is an event such as two lineages at generation t share the same ancestor at generation t-1, which defines a bifurcating node in the genealogy of individuals. Generations in the model are discrete and non-overlapping, and a single coalescence event can happen at a given generation. When the number of sampled individuals at present is such as $n \ll J_m(t)$, the distribution of coalescence times can be approximated as an exponential law with parameter λ proportional

thereby on the history of regional habitat extant. The variation of $J_m(t)$ is likely to depend on predefined, paleoenvironmentally distinct periods (Ref). 102 In addition, the genealogy depends on spatial structuring and migration dynamics across local assemblages. 103 The coalescent simulator (Kelleher, 2020) used in ecophylo supports a discrete-deme model in which assemblages exchange migrants at given rates supplied in a migration matrix. In a coalescent approach, individuals 105 moving from deme j to k backwards in time actually correspond to individuals migrating from deme kto j forwards in time. Thus the migration rates in the migration matrix represent as the proportion of 107 immigrants received by a given deme at each generation. The migration matrix can be parameterized to 108 encompass a wide range of migration scenarios, and can also depend on t so as to represent changing migration 109 dynamics during biogeographic history. By combining past fluctuations of $J_m(t)$ and migration scenarios 110 across demes, the coalescent-based modelling approach can account for a variety of dispersal and vicariance 111 events hypothesized to have shaped the biogeographic histories of extant ecosystems (Ref gen). The topology 112 of the resulting genealogy then reflects the combined influence of migration and ecological drift in a finite 113 fluctuating environment with possible differing population demographic histories linked by migration. 114

to $1/(2 \cdot \frac{1}{2 \cdot J_m(t)})$ {Wakeley, 2009}. Therefore, the distribution depends on the fluctuation of $J_m(t)$ over time,

115 Phylogenetic reconstruction and species abundances

First, we started by simulating the genealogies of individuals in an assemblage experiencing past demographic fluctuations and/or linked by vicariance or migration events using the ms coalescent simulator (Hudson 2002; 117 Kelleher, 2020), without allotting a species label to each individual. Second, we sprinkle mutation events over the branches of simulated genealogies depending on branch lengths, so that the number of mutations 119 over a branch followed a Poisson distribution with parameter $\mu \cdot B$ where μ is the point mutation rate and B is the length of the branch. The descendants stemming from a branch with at least one mutation defined 121 a genetically distinct clade. Since an extant species should be a monophyletic genetic clade distinct from 122 other species, all paraphyletic clades of haplotypes at present were merged to form a single species. In the 123 UNTB (Hubbell 2001) point mutations instantenously give rise to a new species, in which case all branches 124 descending from a mutation event are merged to form species. Yet, there is a general consensus that the mecanisms behind speciation are more complex and should at the very least spread out over more than 126 a single generation. Thus considering speciation as a drawn out protracted process, whereby groups of genetically distinct individuals should only be recongised as new species after a given period of τ generations 128 (Rosindell 2010) meets more realistic expectations regarding the speciation process. Therefore, monophyletic lineages with distinct genotypes and older than τ generations were considered a distinct species (Manceau et al. 2016). Both options (protracted vs instantenous) speciation models are implemented in the ecophylo library and can be used to derive the phylogenetic relationships among individuals as well as the number of individuals descending from a speciation event in the genealogy, which defined the species abundance in the sample at present.

FIGURE !!

36 Application of the eco-evolutionary model

Here we show how to simulate communities and their phylogenetic relationships for a wide range of past
demographic scenarios having affected species assemblages, using the ecophylo package in Python language.
We also provide ways to produce many simulated datasets from prior distributions of model parameter values,
so as to allow inferring parameter values of actual biodiversity patterns from the comparison of simulated to
observed patterns with Approximate Bayesian Computation (ABC).

Simulating past demographic fluctuations of multiple species

The ecophylo package essentially articulates itself around the ecophylo simulate function. This function implements the above-mentioned simulation algorithm, which provide a phylogeny in Newick format along with corresponding species abundances, for a combination of parameter values representing the past biogeographic history of $J_m(t)$. Each biogeographic event accounting for the history of $J_m(t)$ occurs at a specific time that users must supply in changetime as a list in the order in which they occur. In the following example, an assemblage of species and their phylogenetic relationships are simulated assuming that $J_m(t)$ has fluctuated in the past over 3 predefined periods, from present to 700 generations ago, from 700 to 10000 generations ago, and finally from 5000 generations until a common ancestor is found.

```
import ecophylo
n = 25 #the number of sampled individuals
deme_sizes = [[5000,10000,50000]] # the size of the assemblage in the past, the first element is the cu
mu = 0.001 # the point mutation rate
changetimes = [[0,700,10000]] # the dates (in generation time) at which the assemblage has changed size
tree = ecophylo.simulate(samples = n,
```

```
##
151
152
    ##
                              /-sp1
    ##
                          /-1
153
                      /-1
    ##
                              \-sp2
154
    ##
155
                 /-|
    ##
                          \-sp3
156
                   - 1
    ##
157
                      \-sp4
158
159
    ##
                 \-sp5
160
    ##
161
             \-sp6
162
```

The *getAbund* function allows us to retrieve the number of individuals descending from a speciation event in the genealogy, thus defining the species abundance in the sample at present.

```
abund = ecophylo.getAbund(tree)
print(abund)
```

```
165 ## [5, 3, 2, 6, 7, 2]
```

We can then compute summary statistics on the resulting phylogeny and species abundances. These summary statistics can then be used to compare different eco-evolutionary scenarios having yielded different patterns of extant community composition.

```
import numpy as np

shannon = -sum([a/sum(abund)*np.log(a/sum(abund)) for a in abund if a != 0])

simpson = sum([a/sum(abund)**2 for a in abund if a != 0])

invsimpson = 1/simpson
```

```
print("Shannon-Weaver index = " + str(shannon))

## Shannon-Weaver index = 1.6793741045013952

print("Simpson's diversity index = " + str(simpson))

## Simpson's diversity index = 0.04

print("Inverse Simpson's = " + str(invsimpson))

## Inverse Simpson's = 25.0
```

Simulating multi-species assemblage structure and history

The demographic history of $J_m(t)$ can be further complexified by not only considering demographic fluctuations but also including multiple demes exchanging migrants. Multiple demes can be supplied to the ecophylo.simulate function, by specifying the number of sampled individuals in each deme in list format. In the following section we show how to simulate an assemblage of species and their phylogenetic relationships, whereby multiple demes can fluctuate in size over time and be linked by migration of varying intensity and/or originate from the split of an ancestral deme.

Multiple demes linked by migration

The detailed history of $J_m(t)$ in each deme should be supplied as a nested list in deme_size, along with the corresponding dates in changetimes (in generation time) at which the changes in size occur. In the following example, we consider two demes whose sizes have fluctuated in the past, and which are linked by a symmetric migration rate of 0,7. This means that at each generation 70% of individuals from each deme come from the other.

```
samples = [5, 10] # the number of sampled individuals in each deme

deme_sizes = [[1000,2500],[4000,5000,6000]] # the sizes of the demes in the past, again the first eleme

changetimes = [[0,100], [0,300,400]] # the dates in the past (in generation time) at wich each demes ha

migr = 0.7 # the symmetric migration rate between demes
```

```
##
185
    ##
                      /-sp1
186
    ##
187
                    /-sp2
    ##
188
                      \-I
    ##
189
                          \-sp3
190
191
    ##
                      /-sp4
192
    ##
193
                      \-sp5
194
    ##
             \-sp6
196
```

A more complex migration history can be provided, for instance by supplying a migration matrix detailing
each pairwise migration rates between demes or a list of migration matrixes (or symmetric migration rates)
in the case where these have varied in the past. In this case, the dates at which migration has changed
should be provided to ecophylo.simulate using the migr_time parameter. In the following example, migration
between demes is not symmetric, and has changed in the past. Thus, we provide a list of migration matrixes
and a corresponding list of dates, indicating that the migration matrix has changed over time at specified
periods.

```
samples = [5, 10] # the number of sampled individuals in each deme

deme_sizes = [[1000,2500],[4000,5000,6000]] # the sizes of the demes in the past, again the first eleme

changetimes = [[0,100], [0,300,400]] # the dates in the past (in generation time) at wich each demes ha
```

```
migr = [[[0,0.1],
           [0.2,0]]
           [[0,0.3],
           [0.4,0]]
           [[0,0.5],
           [0.6,0]]
           [[0,0.7],
           [0.6,0]]] # the migration matrixes between demes in the past, the first element is the current
   migr_times = [0, 100, 200, 300] # the dates in the past (in generation time) at which the migration rat
   tree = ecophylo.simulate(samples = samples,
                            deme_sizes= deme_sizes,
                            mu = mu,
                            changetimes= changetimes,
                            migr = migr,
                            migr_times = migr_times, seed= 42)
   # tree.render("%%inline")
   print(tree)
   ##
   ##
            /-sp1
         /-1
        | \-sp2
   ## --|
        | /-sp3
         \-I
   ##
   ##
          | /-sp4
          \-|
   ##
212
```

204

205

206

207

209

211

```
213 ## \-sp5
```

In situations with multiple demes, we can compute summary statistics of β diversity. The *getDeme* function allows us to retrieve the deme of the individuals descending from a speciation event in the genealogy and thus species abundances relative to each deme.

```
demes = ecophylo.getDeme(tree)
beta = sum([all([1>0 for 1 in list]) for list in demes]) / len(demes)
beta
```

217 ## 0.6

218 Simulating deme split history #TODO: re-document how to use splits

A description of the deme split history should be provided to ecophylo.simulate using the supplementary vic events parameter to specify whether and how splits in demes may have led to subsequent vicariance. 220 This object should be a nested list containing the details of each split event, containing in order: the date 221 (in generations before present) at which the split occurred, the demes resulting from the split and finally 222 the ancestral deme number. In this example, we consider a situation in which 2000 generations ago, 2000 223 individuals are seperated from an ancestral deme originally containing 6000 individuals to form extant deme 2. 224 Later, 1000 generations ago, the ancestral deme, now containing 4000 individuals splits again to form extant 225 demes 1 and 0. This can be seen, perhaps more easily, in a backward process as demes 0 and 1 merging 1000 generations ago followed by demes 2 and 1 merging 2000 generations ago. 227

Thus, as long as the split dates appear in the correct order in change_time for the corresponding ancestral deme and match the sizes of the ancestral deme in the past provided in com_size, vicariance events can be supplied to *ecophylo.simulate* along with previously mentioned fluctuations in deme sizes as well as varying migration history.

Wether to conduct virtual experiments examining how different eco-evulionary scenarios have shaped patterns

of diversity (Barthelemy et al. 2021) or to carry out inference (Csillery et al. 2010), ecophylo allows simulating large datasets over wide ranges of eco-evolutive parameters. Specifically, the *ecophylo.dosimul* function can

Examining contrasting eco-evolutionary scenarios

233

235

be used to call ecophylo. simulate and retreive summary statistics generated for different parameter values 236 drawn from specified distributions. The parameter format is very similar to that of the ecophylo.simulate 237 function. The nsim parameter is used to specify the number of simulations to run. Then, whether a given 238 parameter for the simulation should be drawn from a prior distribution should be specified by remplacing the parameter value by a list containing in order: the parameter bounds as well as a string specifying the 240 shape of the distribution. The dosimul function then returns a table of sampled parameter values used for the simulations, a table of summary statistics and (if specified) exports the simulated phylogeneties. 242 Let us reconsider our first example in which $J_m(t)$ has fluctuated in the past over 3 predefined periods. Let 243 us say, for the sake of this example, that we wish to simulate what happens when the size of the assemblage between 700 and 10000 generations takes different values. In this case, the corresponding element in comsize 245 should be replaced by a list specifying the bounds (in this example, 5000 and 50000) as well as the desired distribution in which this parameter should be drawn (in this example, a uniform distribution).

```
deme_sizes= deme_sizes,
mu = mu,
changetimes= changetimes)
```

We can then access a table of parameters used for each simulation, in this case with the size of the assemblage over the second time period noted " $deme_sizes_pop0_t1$ " varying uniformily between 5e3 an 5e5.

output[0] # parameters used for the simulations

250	##	samples_pop0	mu	tau	 deme_sizes_pop0_t2	time_pop0_t1	time_pop0_t2
251	## 0	20	0.001	0	 50000	700	10000
252	## 1	20	0.001	0	 50000	700	10000
253	## 2	20	0.001	0	 50000	700	10000
254	## 3	20	0.001	0	 50000	700	10000
255	## 4	20	0.001	0	 50000	700	10000
256	##						

257 ## [5 rows x 8 columns]

We can also retrieve the associated relative species abundances (number of individuals per species) as well as
the number of species per deme for each simulation.

output[1] # summary statistics (abundances and alpha diversity per deme)

```
7
                                                           8
                                                                9
                                                                     10
                                                                         alpha0
260
          3.0
                5.0
                      1.0
                            1.0
                                 2.0
                                       2.0
                                             1.0
                                                  2.0
                                                        3.0
                                                              0.0
                                                                               9
261
                                                              1.0
                2.0
                      1.0
                            1.0
                                 2.0
                                       3.0
                                             1.0
                                                  2.0
                                                        2.0
          2.0
                                                                              11
262
                2.0
                      2.0
                                             2.0
                                                  3.0
           1.0
                            1.0
                                 3.0
                                       1.0
                                                        2.0
                                                              3.0
                                                                    0.0
                                                                              10
263
                            2.0
          5.0
                2.0
                      1.0
                                 4.0
                                       2.0
                                             2.0
                                                  2.0
                                                        0.0
                                                                               8
264
                3.0 1.0 2.0 1.0 8.0
                                             2.0 0.0 0.0 0.0
                                                                               7
          3.0
265
```

The resulting tables can then easily be integrated in further analyses or used for inference, for instance using
Approximate Bayesian Computation (ABC). For users wishing to use the dedicated tools in R language, a
script is provided in the supplementary materials that will allow users to easily import the results of their
simulations in R.

270 Discussion

ecophylo bridges the gap between ecological models representing population and assembly dynamics, and evolutionary models representing the appearance, disappearance of taxa over time. Thanks to great flexibility 272 in parametrization and simplicity in output format, we feel that this freely available Python library meet the need of scientists developing novel eco-evolutionary models to infer, hindcast and forecast biodiversity 274 patterns. 275 Studies in ecology often neglect the influence of evolutionary events, by customarily considering the regional species pool from which communities assemble via rapid local dynamics as a static snapshot of evolutionary 277 history (Lessard et al. TREE 2012). However, recent studies have called for a fuller integration of biogeographic history into community ecology (Swenson 2019, Overcast et al. 2019, 2020), as well as for a more mechanistic 279 understanding and modeling of key processes shaping the composition of species pools (Denelle et al. 2019). 280 With the novel simulation algorithm proposed in the ecophylo package, we explicitly represent how elementary 281 ecological mechanisms such as ecological drift and migration (Vellend 2010) in a finite, temporally variable 282 environment shape evolutionary trajectories and result in extant patterns of phylogenetic and taxonomic 283 diversity. First, our model allows relaxing the assumption of constancy in metacommunity size of the neutral 284 theory of biodiversity (Hubbell 2001), and thus accounts for the discordance of demographic histories between distinct regional species pools with fluctuating sizes over time. This feature is an essential advantage of 286 ecophylo to understand and model the influence of past environmental changes on biogeographic dynamics and biodiversity patterns. Also, modeling speciation as a gradual process by providing a way to delimit 288 extant taxa (Manceau et al. 2015) meets more realistic expectations than considering speciation as an 289 instantaneous event (Rosindell et al. 2010). Secondly, the simulation algorithm proposed in the ecophylo 290 package by decoupling the dynamics of individuals in a fluctuating environment from the speciation process, 291 allows extending the coalescent modeling framework (Kingman 1982, Hudson 1983) to consider multiple 292 species assemblages (Manceau et al. 2015). Thus, ecophylo can be used in the context of phylogeography to 293 investigate the remnant influence of past biogeographic events on several co-occurring taxa (Barthelemy et al. 2021). 295 The dosimul function of the ecophylo package makes it possible to generate patterns of diversity along broad ranges of parameter values reflecting contrasted scenarios of past demographic fluctuations as well as 297 migration and/or habitat fragmentation history having affected multi-species assemblages. An overarching 298 goal in both ecology and evolution is to infer the mechanisms responsible for shaping diversity patterns from

the limited information they contain at present (McGill 2019, Stouffer 2019). By adopting a mechanistic

modeling approach of eco-evolutionary processes, we can first address whether a set of given metrics is 301 sensitive to the mechanisms we chose to investigate by designing virtual experiments. For instance, we can compare large virtual datasets generated over a wide range of parameters, which represent a wide range of 303 biogeographic scenarios we wish to investigate, and then determine which subset of metrics, if any, can keep track of these mechanisms of interest (Barthelemy et al. 2021). For instance, in the case were confounding 305 extant distribution patterns can arise from either vicariance or migration or a combination of both processes, 306 ecophylo can be used to examine patterns of phylogenetic and/or taxonomic diversity simulated over a broad 307 spectrum of scenarios combining migration and vicariance events. It is then possible to assess whether the 308 chosen set of diversity metrics allow distinguishing between the influence of migration versus vicariance (Hastie et al. 2009, Csillery et al. 2012). Second, we can use simulated datasets to carry out inference, that is, 310 retracing the most likely past demographic history of $J_m(t)$ based on the comparison of these datasets to 311 actual extant biodiversity patterns (Csillery et al. 2010). While most existing approaches estimate $J_m(t)$ as 312 the harmonic mean of the per-generation $J_m(t)$ (Etienne 2005), explicitly modeling the temporal variation of $J_m(t)$ should allow investigating the relationship with past environment history. Furthermore, the speciation 314 model itself can add considerable complexity to the demographic model depending on the constraints it 315 imposes on the speciation process, for instance with protraction or the strict respect of monophyly. In these 316 situations, theta has no tractable analytical solutions for a given set of demographic parameters, as it has been 317 largely shown in population genetics. However, with Approximate Bayesian Computation (ABC) methods we 318 can avoid computing the explicit likelihood of the model by approximating it through the relative proximity 319 between the true dataset and datasets simulated given a coalescent model (Csillery 2012, Beaumont 2010, Jabot and Chave 2008). 321

The baseline eco-evolutionary model provided in ecophylo assumes neutrality. That is, species are evenly 322 subject to fluctuations in the size of the assemblage they form with no regards to how individual fitness 323 differences may influence their probability to persist in a given environment or migrate. Increasing the 324 complexity of the model would require accounting for the ways in which deterministic processes such as ecological biotic and abiotic filtering, jointly with evolutionary natural selection, can affect diversification and 326 assemblage dynamics over time (Ewing and Hermisson 2010, Ovaskainen et al. 2011, Karhunen et al. 2013, 327 Manceau et al. 2016). Yet, because of the implications simulating all these elementary mechanisms for all 328 individuals forward in time would have on computation times, we have focused on a coalescent framework 329 (Munoz et al. 2018). Later versions of the ecophylo package should gain in complexity by drawing from recent 330 developments in coalescent simulation algorithms implementing spatially explicit methods (Kelleher et al. 2014 331 ; Rosindell et al. 2008), natural selection (Shlyakhter et al. 2014) or individual/species interactions (Lepers et 332

al. 2021). Yet, for the time being, ecophylo in its initial version, with the flexibility in parameterization
of simulations along with in the choice of summary statistics for ABC analyses, can be used as a neutral
baseline to investigate how elementary mechanisms of mutation, drift and migration in a finite fluctuating
environment influence evolutionary trajectories and thus shape patterns of diversity.

Data accessibility

The *ecophylo* package is available on https://github.com/thegreatlizzyator/ecophylo The *ecophylo* package
can be installed by applying the following command in Python and can then be called into R provided the
prior installation of *reticulate*

pip install ecophylo

Authors' contributions statement

EB conceived the study and built the basic architecture of the *ecophylo* package. EB and MJ did substantial work on adding functionalities, testing and cleaning code. All the authors contributed to setting up the framework and to write the manuscript.

References