



HAL
open science

The Phylogenetic Limits to Diversity-Dependent Diversification

Rampal S Etienne, Bart Haegeman, Álvaro Dugo-Cota, Carles Vilà, Alejandro
Gonzalez-Voyer

► **To cite this version:**

Rampal S Etienne, Bart Haegeman, Álvaro Dugo-Cota, Carles Vilà, Alejandro Gonzalez-Voyer. The Phylogenetic Limits to Diversity-Dependent Diversification. *Systematic Biology*, 2023, 72 (2), pp.433-445. 10.1093/sysbio/syac074 . hal-04219437

HAL Id: hal-04219437

<https://hal.science/hal-04219437v1>

Submitted on 27 Sep 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

The phylogenetic limits to diversity-dependent diversification

RAMPAL S. ETIENNE^{1,*}, BART HAEGEMAN², ÁLVARO DUGO-COTA³, CARLES VILÀ³,

ALEJANDRO GONZALEZ-VOYER⁴ & LUIS VALENTE^{1,5}

¹ Groningen Institute for Evolutionary Life Sciences, University of Groningen, Box 11103, 9700 CC Groningen, The Netherlands.

² Theoretical and Experimental Ecology Station, CNRS and Paul Sabatier University, Moulis, France.

³ Conservation and Evolutionary Genetics Group, Doñana Biological Station (EBD-CSIC), Seville, Spain.

⁴ Department of Evolutionary Ecology. Instituto de Ecología, Universidad Nacional Autónoma de México, Mexico city, Mexico.

⁵ Naturalis Biodiversity Center, Darwinweg 2, 2333 CR Leiden, The Netherlands

*Corresponding author. Email: r.s.etienne@rug.nl. Phone: +31 50 363 2230

Running head: Phylogenetic limits to diversity-dependence

Author contribution: RSE and LV conceived the idea for this paper, RSE and BH worked out the IW model mathematically, RSE implemented the likelihood calculation in the DAISIE package, LV and RSE conducted the bootstrap analyses, ADC, AGV and CV provided the data and expertise on the *Eleutherodactylus* system, ADC prepared the *Eleutherodactylus* phylogeny and distribution maps, and RSE, BH and LV each wrote parts of the manuscript. All authors commented on the manuscript.

ABSTRACT

While the theory of micro-evolution by natural selection assigns a crucial role to competition, its role in macroevolution is less clear. Phylogenetic evidence for a decelerating accumulation of lineages suggests a feedback of lineage diversity on diversification. However, does this feedback only occur between close relatives, or do distant relatives also influence their diversification? In other words: are there phylogenetic limits to this diversity-dependence? Islands form ideal systems to answer these questions, because their boundedness facilitates an overview of all potential competitors. The DAISIE (Dynamic Assembly of Island biota through Speciation Immigration and Extinction) framework allows for testing the presence of diversity-dependence on islands given phylogenetic data on colonization and branching times. The current inference models in DAISIE assume that this diversity-dependence only applies within a

colonizing clade, i.e. all mainland species can colonize and diversify independently from one another. We term this clade-specific (CS) diversity-dependence. Here we introduce a new DAISIE model that assumes that diversity-dependence applies to all island species of a taxonomic group regardless of their mainland ancestry, i.e. diversity-dependence applies both to species within the same clade and between different clades established by different mainland species. We call this island-wide (IW) diversity-dependence. We present a method to compute a likelihood for this model given phylogenetic data on colonization and branching events and use likelihood ratio bootstrapping to compare it to the likelihood of the CS model in order to overcome biases known for standard model selection. We apply it to the diversification of *Eleutherodactylus* frogs on Hispaniola. Across the Greater Antilles archipelago, this radiation shows repeated patterns of diversification in ecotypes which are similar across clades. This could be suggestive of overlapping niche space and hence between-clade interactions, i.e. IW diversity-dependence. But it could also be suggestive of only within-clade interactions, because between-clade interactions would have blocked the same ecotype re-appearing. We find that the CS model fits the data much better than the IW model, indicating that different colonizations, while resulting in similar ecotypes, are sufficiently distinct to avoid interacting strongly. We argue that non-overlapping distributions between clades (both spatially and in terms of ecotypes) cannot be used as evidence of CS diversity-dependence, because this pattern may be a consequence of IW diversity-dependence. By contrast, by using phylogenetic data rather than distributional data our method does allow for inferring the phylogenetic limits to diversity-dependent diversification. We discuss possibilities for future extensions and applications of our modelling approach.

Key words: birth-death model, diversity-dependence, *Eleutherodactylus*, Caribbean, adaptive radiation, island biogeography

INTRODUCTION

“As species of the same genus have usually, though by no means invariably, some similarity in habits and constitution, and always in structure, the struggle will generally be more severe between species of the same genus, when they come into competition with each other, than between species of distinct genera”. This statement by Darwin in the *Origin of Species* (Darwin, 1859), known as the competition-relatedness hypothesis (Cahill et al., 2008) or the phylogenetic limiting similarity hypothesis (Violle et al., 2011), or Darwin’s naturalization hypothesis in the field of invasion biology (Proches et al., 2008), has been the subject of debate over the past decades, particularly in the field of phylogenetic community ecology (Mayfield and Levine, 2010; HilleRisLambers et al., 2012; Pigot and Etienne, 2015; Gerhold et al., 2015;

54 Narwani et al., 2015; Germain et al., 2016; Cadotte et al., 2017; Wilcox et al., 2018). The consequences
 55 of the competition-relatedness hypothesis for macroevolution have received much less attention. Darwin
 56 (1859) formulated these consequences himself as “each new variety or species, during the progress of its
 57 formation, will generally press hardest on its nearest kindred, and tend to exterminate them.” This
 58 implies that with increasing diversity, speciation rates decline or extinction rates increase. This
 59 phenomenon has been referred to as diversity-dependent diversification (also somewhat confusingly called
 60 density-dependent diversification) since the 1970s (Raup et al., 1973; Walker and Valentine, 1984).
 61 Rabosky (2013) distinguishes Darwinian diversity-dependence, which does not imply an upper bound,
 62 from asymptotic diversity-dependence, which by definition does impose an upper bound on diversity. We
 63 leave the question aside whether an upper bound exists, and rather focus on the commonality of these
 64 types of diversity-dependence: that diversity levels affect diversification, and in particular colonization
 65 and speciation rates decline with increasing diversity. (In other words: even though in this paper we
 66 model this negative diversity-dependence with a finite upper bound, we do not believe that whether the
 67 diversity limit is finite or infinite is crucial for our findings.)

68 There have been many suggestions of how such diversity limits come about (Rabosky, 2013;
 69 Rabosky and Hurlbert, 2015). Here we do not enter this discussion, but we are interested whether there
 70 is a phylogenetic limit to the effect of diversity, i.e. whether diversity-dependence only acts between
 71 closely related species or (also) between distantly related species. There is considerable support for
 72 diversity-dependence in clades of phylogenetically closely related species (Foote and Miller, 2006;
 73 Phillimore and Price, 2008; Rabosky and Glor, 2010; Etienne et al., 2012; Jönsson et al., 2012; Foote
 74 et al., 2018), but there is also some evidence that phylogenetically distantly related (but ecologically
 75 similar) taxa reduce each other’s diversification rates (Stanley, 1973; Sepkoski, 1996; Valkenburgh, 1999;
 76 Jablonski, 2008; Silvestro et al., 2015; Pires et al., 2017). However, the latter evidence is relatively scarce
 77 and comes mostly from fossil data. The question then presents itself whether molecular phylogenies can
 78 also inform us about the phylogenetic limits to diversity-dependent diversification.

79 We propose that islands are the ideal arena to study these questions, because they are clearly
 80 defined systems where (exceptional) radiations have occurred. Moreover, as islands tend to be
 81 depauperate, we see cases where species released from competition have radiated to fill niches usually
 82 occupied by a different clade, e.g., woodpecker finches in the Galápagos. In MacArthur & Wilson’s
 83 original work on island biogeography (MacArthur and Wilson, 1967) speciation receives little attention
 84 and therefore also diversity-dependent speciation, but colonization and extinction are
 85 diversity-dependent in their theory, as per capita colonization rates decrease and per capita extinction

rates are assumed to increase with increasing island diversity. The General Dynamic Model of island biogeography (Whittaker et al., 2008) explicitly assumes that the island's carrying capacity influences the diversification rates. However, neither of these classic works discusses the phylogenetic nature of the limits to diversification. Here, we consider two types of diversity-dependence, differing in the phylogenetic extent of diversity-dependence: the clade-specific (CS) level, where only species that descend from the same mainland (extinct or extant) species (possibly through multiple colonizations) reduce each other's speciation rate and colonization rates, and the island-wide (IW) level, where all island species of a predefined taxonomic group, that may descend from very different mainland ancestors, inhibit each other's speciation and colonization (see Fig. 1). Our focus is on species that occur on the island, and therefore by 'clade' we refer to a lineage of island species descending from the same mainland ancestor species. These island lineages are evidently embedded in a wider lineage containing both insular and mainland species, but the phylogeny of the species outside of the island is not considered here. The CS scenario can be modelled by assuming a carrying capacity or upper limit to the number of species for each clade, while the IW model can be modelled by assuming an island-wide carrying capacity or upper limit to the total number of species. The CS and IW models are thus two extremes of a continuum of diversity effects on colonization and speciation. In practice, these effects will not stop directly at the clade established by a colonizing species as in the CS model, but they will also not generally extend to all island species of the considered taxon as in the IW model. Modelling the continuum between the extremes taking into account the phylogenetic (or phenotypic) distances between the mainland species would be ideal, but the IW model is already difficult to handle mathematically and computationally (see below), and thus modelling an intermediate case is currently unfeasible. However, we believe that with these two extremes we are still able to gain more insight into the phylogenetic limits to diversity-dependent colonization and speciation.

Diversity-dependence in speciation rates and colonization rates has been incorporated in the DAISIE framework (Dynamic Assembly of Island biota through Speciation, Extinction and Immigration, Valente et al. (2015)) that allows maximum likelihood estimation of rates of colonization, speciation and extinction from phylogenetic data of the clades that colonized an island (or archipelago). In the first simulations in this framework, diversity-dependence was of the IW-type (Valente et al., 2014). For inference (i.e. parameter estimation), only the CS model was implemented (Valente et al., 2015), using insight from analyses on single clades of closely-related species (Rabosky and Lovette, 2008; Etienne et al., 2012), because the IW model presented technical difficulties. Here we overcome (some of) these technical difficulties by presenting a method to compute the likelihood of colonization and branching

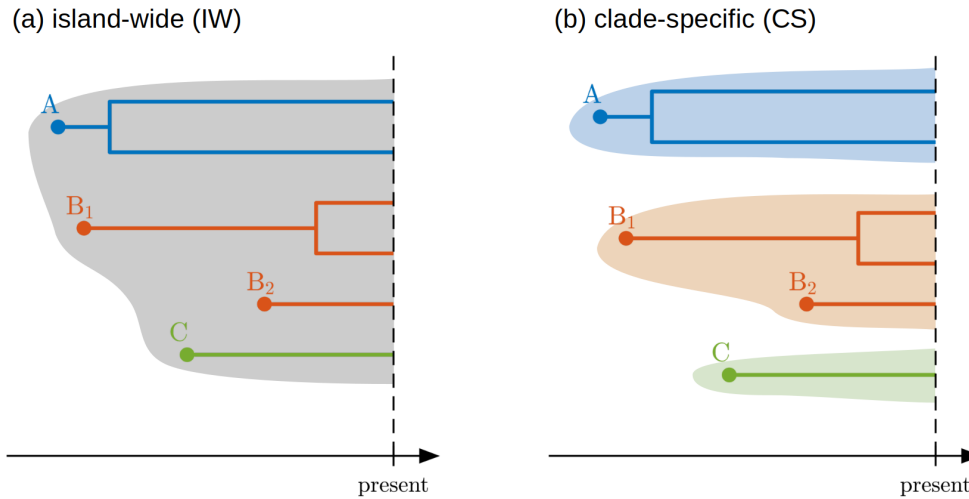


Figure 1. Schematic representation of the two types of diversity-dependence. Phylogenetic trees A to C represent clades of island species descending from different colonization events. In the IW model (a) diversity-dependence extends to all island lineages in the data, whereas in the CS model (b) diversity-dependence extends only to species descending from the same mainland species. In this example there is a recolonization of species B. In the CS model diversification in clade B₁ depends on diversity in clade B₁ as well as clade B₂, because these two clades descend from the same mainland ancestor (in a phylogeny that includes exclusively the island species, clades B₁ and B₂ would form a single monophyletic lineage). This is evidently also true for the IW model. For the CS model the same clade-level carrying capacity K applies to each clade separately (represented by the different colours of the shaded areas), while for the IW model it applies to all clades together.

118 events under the IW model.

119 We illustrate our method with an application to the colonization of Hispaniola by five lineages of
 120 *Eleutherodactylus* frogs (genus *Eleutherodactylus*; Dugo-Cota et al., 2019), for which both CS and IW
 121 models can be verbally argued to apply. On the one hand, these lineages show, across the Greater
 122 Antillean archipelago, repeated patterns of diversification into a similar set of ecotypes (Dugo-Cota
 123 et al., 2019), suggesting a limited set of niches is available, which in turn implies that
 124 diversity-dependence acts, but no further than within each clade (CS). On the other hand, the relatively
 125 low geographic overlap in ecotypes between clades on Hispaniola suggests that diversity-dependence
 126 extends to all *Eleutherodactylus* species on the island (IW) because species may have blocked
 127 colonization of the same ecotype regardless of their phylogenetic relatedness. Our analysis, using only
 128 phylogenetic data, shows that the CS model fits the data much better than the IW model. We discuss
 129 this result and provide suggestions for further research avenues.

130 METHODS

131 Under the original DAISIE inference model (Valente et al., 2015) and its subsequent extensions (Valente
 132 et al., 2017a,b, 2019) species can colonize an island at a rate γ , go extinct at a rate μ , and speciate via
 133 cladogenesis (when one island species splits into two, forming two new endemic species) at a rate λ^c or
 134 via anagenesis (when one island species diverges from its mainland ancestor becoming a new endemic

species, without leading to an increase in diversity on the island) at a rate λ^a . CS-type
diversity-dependence is implemented by allowing for rates of cladogenesis and colonization to decline
with increasing diversity within a clade, with the number of species within each clade being limited by a
CS carrying capacity, K . The maximum-likelihood implementation of DAISIE allows γ , μ , λ^c , λ^a and K
to be estimated based on the distribution of times of island colonization and branching times within an
island, extracted from divergence-dated molecular phylogenies. A diversity-independent model (DI) is
also implemented, i.e. by fixing K to infinity so that λ^c and γ do not decline with diversity.

A logical alternative model to CS in the island context is the IW model, where instead of a K per
clade there is an island-wide K that determines the maximum number of species that can coexist on an
island across all clades. This model was implemented in the first version of DAISIE, but only in
simulations (Valente et al., 2014). Until now, estimating parameters of an IW model has not been
attempted, because a) the model equations are rather cumbersome to write down and implement, and b)
parameter estimation is computationally demanding in terms of memory requirements and runtimes,
even for small data sets. Here we take on these hurdles. We develop a method of estimating parameters
of an IW model from phylogenetic data. The data requirements, parameters and simulation approach of
the DAISIE IW model are the same as for CS, except that diversity-dependence in λ^c and γ is
determined by an island-wide K , so that these rates decline with diversity of all island species rather
than simply diversity of the colonist clade they belong to.

Likelihood of colonization and branching data for the IW model

We compute the likelihood of the data, consisting of colonization and branching events, for the IW model
using the Q -approach (Etienne et al., 2012; Laudanno et al., 2019). This approach is named after the
quantity $Q(t)$, which is the probability that a random realisation of the model is consistent with the data
up to an arbitrary time t . In the supplementary material we construct the differential equations
governing the dynamics of $Q(t)$, and explain how these equations, which apply to the dynamics between
colonization and branching events, are connected to one another across the colonization and branching
events. By solving these equations from the island emergence time to the present, we obtain $Q(t_p)$, the
quantity $Q(t)$ evaluated at the present time t_p , from which the likelihood can be extracted (see
supplementary material for details).

Our computational procedure is based on the assumption that we have full information about the
extant species. That is, we assume that the island phylogenies of the full set of extant species are known,
together with the corresponding colonization times. This assumption simplifies not only the likelihood

computation, but also the comparability with the CS likelihood. Indeed, in case of partial sampling from the phylogeny, the CS model distinguishes to what clade the missing species belong, while the IW model does not, making their likelihood incomparable. To guarantee full comparability we have also treated the likelihood of the CS model as a product of IW likelihoods with mainland pool size of 1 across the M mainland species. That is, CS and IW only differ in whether clades established by mainland ancestors are independent (CS) or are connected through each other's diversity (IW).

Model fitting

We fitted five DAISIE models: a model without diversity dependence (DI, 4 free parameters), a model with clade-specific diversity dependence (CS-DD, 5 free parameters), a model identical to CS-DD but without anagenesis (CS-DD-noA, 4 free parameters); a model with island-wide diversity dependence (IW-DD, 5 free parameters), and a model identical to IW-DD but without anagenesis (IW-DD-noA, 4 free parameters). In all DD models the per capita rates of cladogenesis λ_N^c and colonization γ_N were assumed to linearly decline with diversity:

$$\lambda_N^c = \lambda_0^c(1 - N/K)$$

$$\gamma_N = \gamma_0(1 - N/K)$$

where N is the total number of species in a clade in the CS model, and the total number of species on the entire island in the IW model. K is the carrying capacity per clade for the CS model (hence the same for each clade) and for the entire island for the IW model. We follow the original DAISIE model (Valente et al., 2015) by assuming no diversity-dependence in extinction or anagenesis, and we solely focus on diversity-dependence in rates of colonization and cladogenesis.

Phylogenetic data

We used the dated phylogeny of *Eleutherodactylus* frogs by Dugo-Cota et al. (2019), which is based on four mitochondrial and three nuclear genes. The data set comprises 152 species of the genus, including 148 Caribbean species, i.e. 89% of the Caribbean diversity, as well as four continental species. The divergence dated phylogeny was reconstructed in BEAST v1.8.2, using secondary time calibration points extracted from the wider eleutherodactyline phylogeny of Heinicke et al. (2007). Dugo-Cota et al. (2019) reconstructed the biogeographical history of Caribbean *Eleutherodactylus* using BioGEOBEARS (Matzke, 2013, 2014) with a time-stratified analysis and nine geographical regions. They inferred five colonizations of Hispaniola from the mainland and surrounding islands (which are collectively referred to

as the mainland hereafter), each of which radiated on the island, to a great or lesser degree, producing five in situ radiations of 28, 21, 8, 5 and 3 species (Table 1).

The Dugo-Cota et al. (2019) phylogeny includes 57 of the 66 Hispaniola species. Because fitting the IW model assumes complete sampling of the extant species of the focal island, we inserted the missing Hispaniola species by assigning them at random locations within the Hispaniola subclades that they have been hypothesized to belong to. Information on the nine missing species and the detailed rationale for including them in a given subclade are given in supplementary Table S1. There is no genetic data available on GenBank for these missing species, because they have been recently described, are known from a single specimen or are possibly extinct. We used a set of functions from the phytools R package to assign missing species to clades (Revell, 2012). Four of the missing species were previously considered subspecies, and have recently been elevated to species, and we thus randomly inserted them at any height along the tip branch of the species they were previously assigned to. Four other species have been proposed to belong to well-defined terminal clades based on morphology, and we randomly inserted them at any position and at any height within those clades. We repeated this procedure 100 times on the five clades from the maximum clade credibility tree from BEAST, producing 100 sets of five clades with complete sampling. The exact procedure is detailed in Table S1. One of the missing species, *E. neiba* was not added to the tree because there is no previous hypothesis regarding its phylogenetic position. We ran a sensitivity analysis including this species as a separate colonization, to assess whether in the unlikely case it formed a separate clade this would affect the results. These analyses showed that even if *E. neiba* formed an independent colonization, the same model would still be preferred. We therefore did not include it in the analyses, as it is unlikely to modify the main findings.

We extracted colonization and branching times for each of the five Hispaniola radiations from these data. Colonization times were assumed to be the stem ages of the Hispaniola clades, as the stem age marks the divergence from the mainland sister clade (which is assumed to be due to the colonization event). Information on each of the Hispaniola clades is given in Table 1 and the phylogeny is shown in Fig. 2.

As the downstream DAISIE analyses are computationally demanding, we wanted to use only one data set for subsequent analyses. In order to perform an informed selection of the tree, we fitted the CS and the IW model with no anagenesis to each of the 100 sets of trees. The results of the analysis on the 100 sets of trees are shown in Table S2. The preferred model in all trees was CS. We thus used only tree set 52, which was the one with the highest likelihood for CS, for all subsequent analyses (hereafter ‘empirical data set’). This may seem to introduce a bias in favor of the CS model, but we note that all

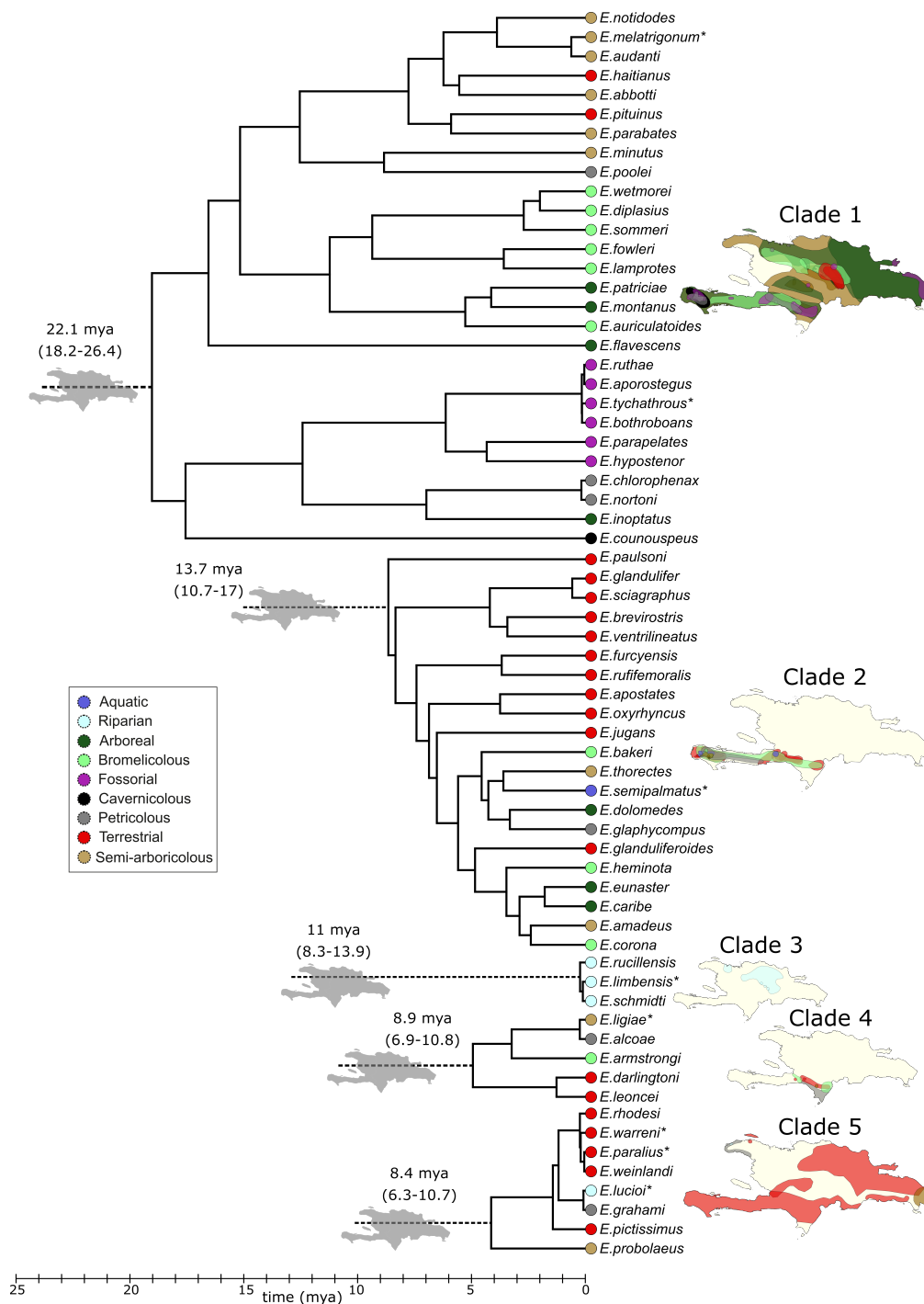


Figure 2. Phylogeny of the Hispaniola *Eleutherodactylus* frogs, and the ecotypes and spatial distribution of the tip species. A separate time-calibrated phylogenetic tree is shown for each of the five clades. Gray islands show the five inferred independent colonization events of Hispaniola. Colors at the tips of the phylogeny represent the species ecotypes (see legend). The same colors are used to show the species distributions for each independent colonization on the Hispaniola map (for visual clarity some transparency has been applied). The asterisk indicates where missing species have been added to the phylogeny according to taxonomic information, see Table S1. We note that our inference method only uses the phylogenetic information in the data, i.e. only the colonization and branching events.

219 loglikelihood differences (and all parameter estimates) were very similar across the 100 sets of trees: the
 220 loglikelihood differences between CS and IW were between 5.2 and 6.6 with a median of 5.9 and set 52
 221 had a loglikelihood difference of 6.4. All 100 data sets would have led to the same conclusions in our
 222 model comparison (see Results). All sets of trees and corresponding DAISIE colonization/branching time

Table 1. Characteristics of the five clades on Hispaniola: diversity, colonization times and geographical distribution within the island of Hispaniola.

Clade	Number of species	Colonization time (Ma)	Geographical distribution
1	28	22.09 (18.21 – 26.36)	Mixed
2	21	13.75 (10.73 – 16.97)	100% South
3	3	11.03 (8.31 – 13.89)	100% North
4	5	8.85 (6.91 – 10.8)	100% South
5	8	8.43 (6.3 – 10.73)	87.5% North

R objects are provided in the supplementary material. The simulation code, functions to compute the likelihood under the two models, and a tutorial on how to run simulations and perform model-fitting are available in the R package DAISIE on CRAN and on Github (<https://github.com/rsetienne/DAISIE>).

Likelihood optimization on the empirical data

We fitted each of the five DAISIE models 5 times to the empirical data set using different random sets of starting parameters to avoid being trapped in local likelihood optima. We assumed an island age of 30 million years, consistent with the paleogeographical reconstruction of Iturralde-Vinent (2006) for when Hispaniola was isolated from other landmasses. The mainland pool size M was set to 1000 frog species. We note that this value is not crucial, because mainland pool size affects only the rate of colonization; the product of mainland pool size and the rate of colonization, i.e. the total rate of colonization, is practically constant (Valente et al., 2019). Indeed, parameter estimates were very similar for optimizations with $M = 300$.

Maximum likelihood optimizations were run on the high-performance (Peregrine) cluster of the University of Groningen. Optimization of DI and CS-type models generally converged in a few hours. IW-DD model optimizations took between a few hours up to 10 days to complete.

Goodness-of-fit

We simulated 5,000 data sets using the maximum likelihood parameters of the preferred CS-type model (CS-DD no anagenesis) and preferred IW-type model (IW-DD no anagenesis), hereafter the CS and IW models. We then plotted relevant statistics from the simulated data sets and compared them to those in the empirical data to study how well the models fit the data.

Bootstrap analysis

We computed the AIC and BIC values and weights for model comparison, but because model selection involving diversity-dependent models is known to be troublesome (Etienne et al., 2016), we used a parametric bootstrap likelihood ratio test similar to Boettiger et al. (2012). This bootstrap analysis additionally allowed us to assess bias and precision of parameter estimates. We chose the first 1000 out of the 5000 data sets from each of the CS and IW simulations. Not all 5000 simulated data sets were used for the bootstrap likelihood ratio test, because the subsequent analyses on these data sets were computationally demanding. For each of the chosen 2000 data sets we fitted both CS and IW models, resulting in a total of 4000 maximum likelihood optimizations. As starting values of the optimizations we used the maximum likelihood parameters of the given model obtained for the empirical data, to make it as likely as possible that we will find the global likelihood optimum, as it is expected to be around these empirical maximum likelihood parameters. To really ensure local optima are avoided, the optimizations would need to be run many times from many different starting values, but this was computationally unfeasible. In some cases it was not possible to use the parameters obtained in the optimization analyses as initial parameters for the optimization. For instance, if a clade in data sets generated under the IW model had more species than the value of K estimated for the CS model fitted to the empirical data, using that K as a starting value to fit the CS model to the IW-simulated data would give a likelihood of 0. Therefore we calculated the starting K for each data set using the largest value of either the K estimated from the empirical data for the given model being fitted, or the maximum number of species in a clade (CS model) or the total number of species on the island (IW model) in the simulated data set.

For the bootstrap likelihood ratio test we compared the logarithm of the likelihood ratio of CS and IW in the empirical data (i.e. loglikelihood difference, loglikelihood of the CS model – loglikelihood of the IW model) with the distribution of the logarithm of likelihood ratios from the data sets simulated under CS and under IW (1000 data sets each). We computed the 95th percentile of the distribution under the IW model. If the loglikelihood difference of the empirical data falls to the right of this value, then they are unlikely to be produced by the IW model, and if it is well within the distribution of the data generated under the CS model, the CS model is selected. We also computed the 5th percentile of the distribution under the CS model. If the loglikelihood difference of the empirical data falls to the left of this value, then they are unlikely to be produced by the CS model, and if it is well within the distribution for the data generated under the IW model, the IW model is selected. If the loglikelihood difference of the empirical data falls between the two percentiles, then no model can be selected decisively.

RESULTS

Likelihood optimization on the empirical data

Convergence of the five independent optimizations per model to the empirical data set was very good, with all five runs finding the same maximum likelihood parameter set for each model. The preferred model using both AIC or BIC was CS-DD with no anagenesis (four free parameters) (Table 2). The loglikelihood difference between the best CS model and the best IW model (both diversity-dependent) was 6.43. This value points to the CS model as the best model also in the likelihood ratio bootstrap test (see below). The models without anagenesis had virtually the same parameter values as their counterparts allowing anagenesis to be different from 0. That is, the latter models had estimated rate of anagenesis that were very close to 0. This is to be expected because all five frog clades radiated and hence there is no evidence for anagenesis. The only signal of anagenesis in such a case could come from the observation of recolonizations of the same mainland species that established the clade(s). This is because the model assumes that recolonizations can only occur after speciation has taken place (if it happens before speciation takes place, the recolonization is assumed to reset the colonization time and is then not observed). As the data did not contain recolonizations, the maximum likelihood estimate of anagenesis is expected to be 0. Across the 100 sets of empirical trees the loglikelihood difference between the diversity-dependent CS and IW models ranged from 5.16 to 6.63, all of which suggest the CS model is highly preferred.

Table 2. Maximum likelihood parameter estimates and corresponding loglikelihood (LL) for five fitted models. DI: diversity-independent rates; DD-CS: clade-specific diversity-dependence in colonization and cladogenesis; DD-CS-noA: same, but with anagenesis rate fixed to 0; DD-IW: island-wide diversity-dependence in colonization and cladogenesis; DD-IW-noA: same, but with anagenesis rate fixed to 0. An asterisk indicates that the estimated value is practically 0. df: degrees of freedom, i.e. number of free parameters; AIC: Akaike information criterion; BIC: Bayesian information criterion.

model	λ_0^c	μ	K	γ	λ^a	LL	df	AIC	AIC weight	BIC	BIC weight
DI	0.18	0.03	∞	0.0002	0*	-215.87	4	439.75	0.00	445.53	0.00
DD-CS	0.44	0.11	36.44	0.0002	0*	-208.67	5	427.34	0.27	434.58	0.15
DD-CS-noA	0.44	0.11	36.45	0.0002	0	-208.67	4	425.34	0.73	431.13	0.85
DD-IW	0.40	0.17	131.89	0.0003	0*	-215.10	5	440.20	0.00	447.43	0.00
DD-IW-noA	0.40	0.17	131.96	0.0003	0	-215.10	4	438.20	0.00	443.98	0.00

Goodness-of-fit

Using the estimated parameters for the diversity-dependent CS and IW models we generated simulated data for which we computed several summary statistics. The distributions of the summary statistics across these simulations fitted well with the empirical data for both models, but somewhat better for the

296 CS model. (Fig. 3, Fig. S1, Fig. S2), as the empirical statistics and the medians across the simulations
 297 are slightly more similar for this model.

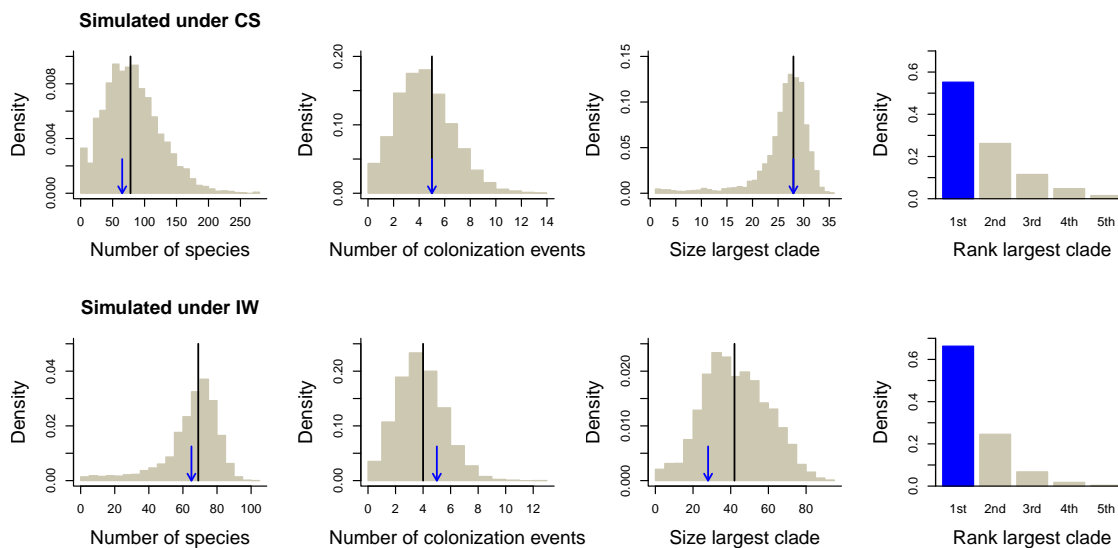


Figure 3. Goodness-of-fit plots. Distributions of relevant metrics (number of species, number of colonizations leading to extant clades, size of the largest clade, and rank of the largest clade when clades are ordered according to their colonization time, rank 1 corresponding to the first colonization) obtained from 5,000 data sets simulated with the maximum likelihood parameters of the CS (top row) and IW (bottom row) models. Black line: median value, blue arrow and blue bar: value in the empirical data.

298

Bootstraps

299 The analyses fitting the CS model to each of 1000 CS and 1000 IW simulated data sets all completed
 300 successfully. For the analyses fitting the IW model to the same data sets, some runs could not be
 301 completed within the limit we set (10 days). For the CS simulated data sets this was 0.8% of the
 302 simulations and for the IW simulated data sets this was 1.6%. These were all data sets with little
 303 information (only a single clade) where the estimation procedure went to very high values of the rate of
 304 cladogenesis and colonization. We used the loglikelihood that was obtained after 10 days which is thus an
 305 underestimate of the maximum IW loglikelihood, but the ML may not be much higher than this value
 306 after 10 days. However, even if we make the unlikely assumption that in all of these aberrant simulated
 307 data sets the IW model is a better fit, they are so rare that our qualitative conclusion that the CS model
 308 is a better fit does not change.

309 Parameters were estimated with high precision and little bias under both models: the median and
 310 means of the distribution of parameters estimated under the CS and IW models for data sets simulated
 311 under those models closely matched the simulated values (Figs. 4 and 5). When fitting the CS model to
 312 IW simulations (Fig. S3) we observe that the K is estimated to be much higher than in the CS
 313 simulations (Fig. 4). This is because the IW simulations show more variability in clade sizes that can

314 only be accommodated by the CS model by assuming a larger clade-level K . When fitting the IW model
 315 to CS simulations (Fig. S4), we do not observe such a discrepancy. Indeed, in this case the total number
 316 of species matters rather than the number of species per clade. All parameter estimates and
 317 corresponding loglikelihoods are available in Table S3.

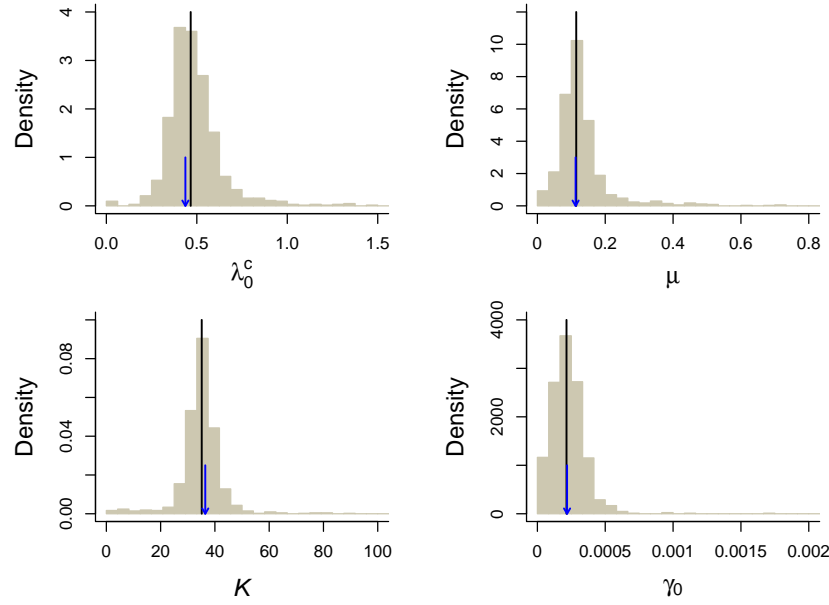


Figure 4. Bootstrap precision estimates of the parameters of the CS model. In a parametric bootstrap analysis the CS model was fitted to 1000 data sets simulated with the maximum likelihood parameters of the CS model for the empirical data. The panels show density histograms of the estimated parameters. The black lines indicate the median estimated values across all simulations and the blue arrows point to the values used in the simulations.

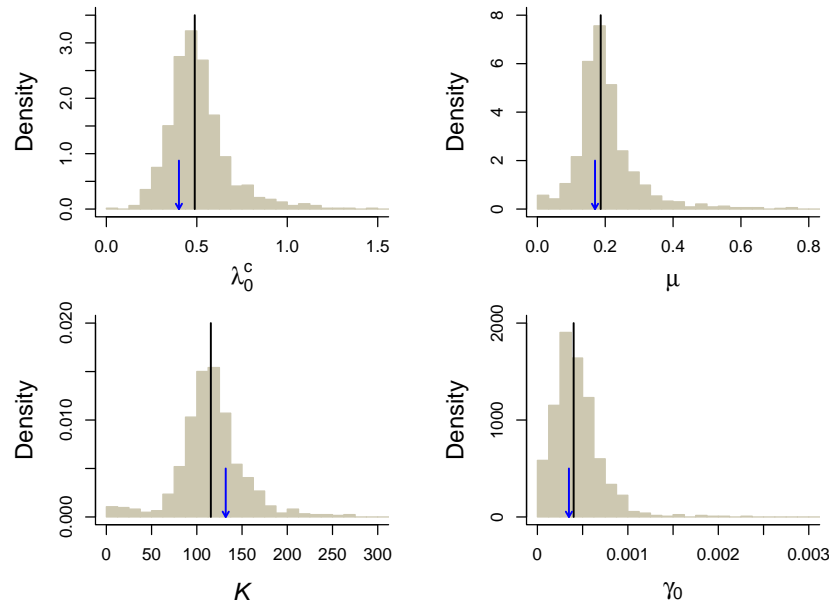


Figure 5. Bootstrap precision estimates of the parameters of the IW model. In a parametric bootstrap analysis the IW model was fitted to 1000 data sets simulated with the maximum likelihood parameters of the IW model for the empirical data. The panels show density histograms of the estimated parameters. The black lines indicate the median estimated values across all simulations and the blue arrows point to the values used in the simulations.

318 The simulated data can be used to check the reliability of model selection (because we know the

generating process). When performing model selection by simply selecting the model with the highest likelihood, the IW model was incorrectly preferred over CS in 7.7% of data sets simulated under CS. The CS model was incorrectly preferred over IW in 19% of data sets simulated under IW. When imposing at least two log-units of difference before selecting a model, these numbers become 0.9% and 1.6%, respectively. The CS and IW model were then correctly selected in 77% and 40.6% of the corresponding data sets respectively, leaving 22.1% and 57.8% undecided between the two models. Because using highest likelihood or higher by at least two log-units is quite arbitrary, and still leads to either high type I error (highest likelihood) or low power (two log-units difference), we used the bootstrap likelihood ratio (or loglikelihood difference) distribution to set the permissible type I error to 5% (two left-most arrows in Fig. 6). This distribution of differences in loglikelihood between the CS and the IW model revealed that it was highly unlikely ($p < 0.001$) that the empirical loglikelihood difference (6.43) would have been found if the underlying model was IW, because the loglikelihood difference found in the empirical data (black arrow in Fig. 6) falls clearly beyond the tail of the distribution of loglikelihood differences obtained from data simulated under IW (higher than the largest likelihood), but falls right in the middle of the distribution of differences for data simulated under CS (at the 49.6th percentile). This all suggests that the CS model is strongly supported as the best model for the empirical data.

The power to select the generating model is relatively high. The power to detect CS is 85% (part of distribution generated under CS model that is larger than the middle arrow in Fig. 6) whereas the power to detect IW is 72% (part of distribution under IW model that is smaller than the left-most arrow in Fig. 6). If the empirical data had had a loglikelihood ratio between -0.29 (the leftmost arrow in Fig. 6) and 1.11 (middle arrow in Fig. 6), model selection would have been indecisive.

DISCUSSION

We have developed a method to determine, using phylogenetic data on island colonization and branching times, whether diversity-dependence in rates of colonization and speciation is limited to species within a clade, or extends to species from different clades, or whether the information in the data is too limited to make a clear call. In Hispaniolan *Eleutherodactylus* frogs we find that models including diversity-dependence outperform models without a negative feedback of diversity on colonization and speciation rates, suggesting that diversity limits play an important role. Diversity limits operating at the clade-specific level (i.e. species from different colonizing clades do not interact) predominate over limits at the island-wide level (i.e. species from different clades reduce each other's rate of colonization and speciation), because the model with clade-specific diversity-dependence clearly outperformed the model

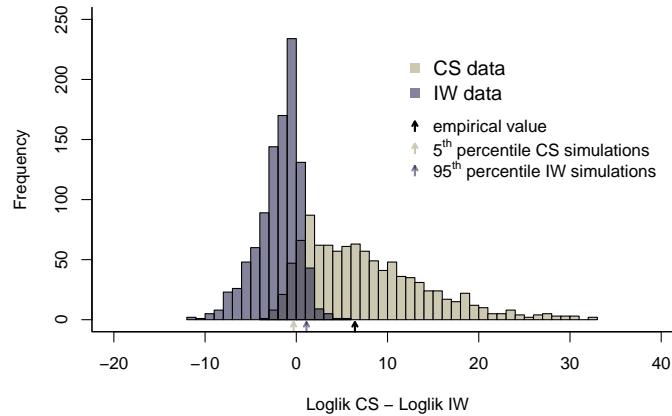


Figure 6. Likelihood ratio bootstrap test. Distribution of differences between the loglikelihood of the CS model and the loglikelihood of the IW model when fitting both models to data sets simulated under CS and IW. The rightmost (black) arrow shows the difference in the empirical data, while the leftmost and middle arrows indicate the 5th percentile and the 95th percentile of the distributions generated under the CS model and the IW model respectively. The black arrow falls well inside the distribution for data simulated under CS, and to the right of the 95th percentile (in fact even the maximum!) of the distribution for data generated under IW. Therefore, the CS model is strongly preferred.

with island-wide diversity-dependence.

Although *Eleutherodactylus* frogs show repeated patterns of evolution into the same set of ecotypes (Dugo-Cota et al., 2019), these results suggest that these ecotypes do not interfere with each other across clades. One could argue that Fig. 2 already tells us this because the overlap in ecotypes and in ranges between the clades on Hispaniola is limited, and hence species do not seem to interact across clades. However, one can also explain this pattern as a *consequence* of interaction across clades, because under IW earlier clades block later ones from radiating into the same habitats (both ecologically and spatially). Our results do not support this explanation and lead us to conjecture that there has been sufficient (niche) space that IW diversity-dependence does not occur. Of course, this may change in time: if we wait millions of years, (niche) space may eventually become saturated, but currently there is no signal of IW diversity-dependence. In summary, present-day spatial distributions and ecological distributions into ecotypes cannot be taken as evidence that species from different clades do not interact, as these patterns may be a consequence of such interactions in the past. The approach we have taken in this paper is to infer such diversity-dependence from the phylogenetic branching pattern. We have shown that if IW diversity-dependence operates, we would often pick up its signal from the phylogenetic data. In our *Eleutherodactylus* frog example, we did not, as there is only 1% chance that the pattern we observed would be generated by an IW model (i.e. only 1 in 100 simulations of an IW model we would obtain a loglikelihood ratio between CS and IW models which is equal or higher than observed for the empirical data).

Our simulations were limited to the parameters estimated from the *Eleutherodactylus* frog data. To assess the more general ability of our approach to identify CS and IW when they are operating would require analyzing many more simulated data sets for a wide range of parameters sets. This is currently computationally unfeasible, because the likelihood maximizations, although performed with highly optimized code, take quite a bit of time (at least a few hours per data set), which bars extensive simulation studies across a sizeable number of replicates. Instead we suggest that researchers wishing to compare CS and IW models for their study system should fit these models to their data and take the estimated parameters to run simulations, just like we did here. This allows one to establish whether CS and IW models can be distinguished by plotting figures such as Fig. 6. We have shown that it is important to do so, because model selection based solely on AIC may be biased (Etienne et al., 2016).

The CS model assumes the same carrying capacity K for each clade, which is a constraint to each clade's size, and hence our model selection may be somewhat biased towards IW, which only limits the overall number of species by its K . Because the CS model nevertheless outperforms the IW model, this is not an issue for this study, and it may be indicative of a similar K among clades, which is in line with ecotype space limiting the number of species equally in each clade. Still, models with different K values for each clade could in principle be fitted to the data to confirm this. In practice, however, this is not really feasible, because we are already estimating four or five parameters, and there may not be enough information in a data set of this size to allow for more parameters to be reliably estimated.

We have only considered two models of diversity-dependence: one where diversity-dependence only applies to species within the same clade, and one where it also applies to species of other *Eleutherodactylus* clades establishing on an island. Various other models can be conceived. First, diversity-dependence might apply to *Anurans* species beyond *Eleutherodactylus* or include other amphibians or even non-amphibians. We have chosen the level of *Eleutherodactylus* species as it seems, arguably, the largest group where the assumptions of equal rates of colonization, speciation and extinction are not too strongly violated. Our results indicate that diversity-dependence does not extend to this scale. Second, diversity-dependence could also occur at a higher taxonomic level, i.e. the number of clades, rather than the number of species within them may be limiting further colonization or diversification. Third, the effect of phylogenetic relatedness may also differ for speciation, extinction and colonization. For instance, Pires et al. (2017) found that speciation is mostly affected by within-clade diversity-dependence, whereas extinction is mostly affected by between-clade diversity-dependence. Fourth, one could define phylogenetic limits in terms of actual phylogenetic distances so that we move from a within- and between-clade dichotomy to a more continuous spectrum where some phylogenetically

401 related clades may interact, but more distantly related clades do not. There are no likelihood methods
402 for such models yet. One may have to resort to simulation-based approaches such as Approximate
403 Bayesian Computation (Janzen et al., 2015). These methods need to integrate over all possible
404 trajectories of the clades through time which is not trivial, because the space of these trajectories is
405 extremely high-dimensional.

406 We assumed no diversity-dependence in extinction and anagenesis to focus on the effect on
407 colonization and cladogenesis, and for model and computational simplicity. However,
408 diversity-dependence in extinction and anagenesis is conceivable. For extinction one may assume higher
409 extinction rates for higher diversity. We note that this causes a stronger pull-of-the-present in
410 lineages-through-time plots contrary to what is commonly observed (Phillimore and Price, 2008; Etienne
411 et al., 2012). However, such a pull-of-the-present may not be visible in empirical data, because we fail to
412 account for incipient species (Etienne and Rosindell, 2012). Likelihood methods that incorporate both
413 diversity-dependence and protracted speciation do not yet exist, however. Diversity-dependence in
414 anagenesis is also conceivable, but it may be both negative and positive. High diversity can inhibit
415 anagenesis by limiting the ecological space to evolve into. However, higher diversity might also mean that
416 there is more selective pressure for a species to evolve away from the mainland sister (sub)species.
417 Anagenesis can also occur through drift alone simply due to long-term isolation from the mainland, in
418 which case a diversity effect on anagenesis seems unlikely. One might also argue that if local adaptation
419 is the primary cause of anagenesis, competition with other species (and thus diversity-dependence in
420 anagenesis) is unlikely to prevent anagenesis. In such a scenario the species will probably not establish at
421 all (some adaptation seems necessary to survive in a new environment) which would be accounted for by
422 diversity-dependence in the colonization rate.

423 One may wonder what it is in the branching pattern that allows for selecting one model over the
424 other. An intuitively obvious candidate may be the rank of the largest clade. The IW model can be
425 expected to have the first clade as the largest, because later clades will be suffering from
426 diversity-dependence and hence not be able to grow very large. However, we noticed that the first clade
427 is also almost equally often the largest clade under the CS model (Fig. 3). Hence, a pattern we may put
428 down to incumbency and interclade competition (Silvertown, 2004; Schenk et al., 2013) arises equally
429 prominently under a model without interclade competition. Apparently, in our empirical example time
430 since colonization is a more important determinant of the size of a clade than diversity-dependence. The
431 IW or CS nature of the colonization and diversification process, and thus the presence or absence of
432 priority effects at the macroevolutionary scale, is hidden in a more complex way in the phylogenetic

433 branching pattern that is not easily picked up by simple summary statistics, but is detected by our
434 likelihood ratio test. We do note that the estimate of the island-wide carrying capacity K (132) is quite a
435 bit larger than the number of species present on the island (66), suggesting that the island is still far
436 from saturation under the IW model. Other systems may have a lower K and the effect of priority effects
437 may be relatively stronger. It is an interesting avenue to study whether there is a relationship between
438 the magnitude of these priority effects and invasibility of islands, which may contribute to our
439 understanding of biological invasions (Fraser et al., 2015).

440 The new IW model may also be applicable in other fields, such as epidemiology where it may
441 serve as a tool in understanding spread of an infectious disease, e.g. a virus, in island-like systems such as
442 schools or hospitals. In such systems there may be multiple sources of infections that spread through the
443 local population and can be modelled as colonizations. The carrying capacity is the number of children
444 or patients. The IW model would be the appropriate model if once the host is infected, it builds up
445 immunity against all strains, thus hindering further colonization and diversification. This scenario is
446 most likely if the colonizing strains are phylogenetically related. The CS model would be a better
447 description if a host can be infected by multiple strains, but within each strain there is viral interference
448 (see e.g. Ojosnegros et al. (2010)). This scenario is most likely if the colonizing strains are
449 phylogenetically (and hence functionally) distinct.

450 The CS model implementation allows incomplete phylogenetic information: if the island species
451 are recognized (including their endemicity status), but their colonization or branching times are not
452 known, the model integrates over the possible colonization and branching times. The same principle can
453 be applied to the IW model, but this is currently computationally unfeasible. Sampling colonization and
454 branching times to obtain a complete data set and then repeating the analysis for each sampled complete
455 phylogeny, as we have done, is probably the most straightforward way to get an idea of the impact of
456 phylogenetic uncertainty. Incomplete knowledge due to failure to recognize incipient or cryptic species is
457 a more fundamental problem that the field has not been able to address completely satisfactorily. There
458 are models that can account for this, e.g. the protracted speciation model (Etienne and Rosindell, 2012;
459 Lambert et al., 2014; Etienne et al., 2014), but the mathematical approach to compute the likelihood
460 under this model seems incompatible with the approach used for diversity-dependence models (Etienne
461 et al., 2012; Laudanno et al., 2019). Simulation-based approaches may be the only (long) way to a
462 resolution (Richter et al., 2020).

463 We have provided a new model for island biogeography with diversity-dependent feedback on
464 colonization and diversification occurring between all island species. Our implementation of this IW

465 model has some computational limitations for islands with large numbers of colonizations, particularly if
466 these are non-endemic, but typical insular data sets with a moderate number of colonizations or a high
467 level of endemism (such as our *Eleutherodactylus* frogs) are perfectly feasible. Our single empirical
468 example serves as an illustration to the empiricist how to explore the phylogenetic limits of diversity
469 limits to diversification from phylogenetic data alone despite the limitations of phylogenetic data (Losos,
470 2011). Although this example showed a clearly better fit of the CS model, future applications may reveal
471 different and more nuanced impacts of clade competition on diversification at a wider range of
472 phylogenetic scales. Further extension of our approach to allow integrating ecological data with
473 phylogenetic data (Harmon et al., 2019), for instance to examine simultaneous diversity-dependence and
474 trait-dependence of diversification, is an exciting but challenging next direction.

475 ACKNOWLEDGEMENTS

476 We thank Ally Phillimore for early discussions that provided the original motivation for this study. We
477 thank Pedro Neves, Joshua Lambert, Ally Phillimore, Tanja Stadler and two anonymous reviewers for
478 helpful comments on the manuscript, and Hanno Hildenbrandt for a major improvement in the
479 performance of the DAISIE PACKAGE. We thank the Center for Information Technology of the
480 University of Groningen for their support and for providing access to the Peregrine high performance
481 computing cluster. RSE and LV thank the Netherlands Organization for Scientific Research (NWO) for
482 financial support through NWO-VICI and NWO-VIDI grants, respectively. LV thanks the DFG for an
483 Eigene Stelle grant (VA 1102/1-1). BH was supported by the Laboratoires d’Excellences (LABEX)
484 TULIP (ANR-10-LABX-41). CV thanks the Spanish Government for funding project CGL2016-75227-P
485 within which the data were collected. RSE and BH thank the bilateral French-Dutch Van Gogh Program
486 for funding work visits.

487 REFERENCES

- 488 Boettiger, C., G. Coop, and P. Ralph. 2012. Is your phylogeny informative? measuring the power of
489 comparative methods. *Evolution* 66:2240–2251.
- 490 Cadotte, M. W., T. J. Davies, and P. Peres-Neto. 2017. Why phylogenies do not always predict ecological
491 differences. *Ecological Monographs* 87:535–551.
- 492 Cahill, J. F., S. W. Kembel, E. G. Lamb, and P. A. Keddy. 2008. Does phylogenetic relatedness influence
493 the strength of competition among vascular plants? *Perspectives in Plant Ecology, Evolution and*

- 494 Systematics 10:41–50.
- 495 Darwin, C. 1859. On the origin of species by means of natural selection, or preservation of favoured races
496 in the struggle for life. John Murray, London.
- 497 Dugo-Cota, A., C. Vilá, A. Rodríguez, and A. Gonzalez-Voyer. 2019. Ecomorphological convergence in
498 *Eleutherodactylus* frogs: a case of replicate radiations in the Caribbean. *Ecology Letters* 22:884–893.
- 499 Etienne, R. S., B. Haegeman, T. Stadler, T. Aze, P. N. Pearson, A. Purvis, and A. B. Phillimore. 2012.
500 Diversity-dependence brings molecular phylogenies closer to agreement with the fossil record.
501 *Proceedings of the Royal Society of London B* 279:1300–1309.
- 502 Etienne, R. S., H. Morlon, and A. Lambert. 2014. Estimating the duration of speciation from
503 phylogenies. *Evolution* 68:2430–2440.
- 504 Etienne, R. S., A. L. Pigot, and A. B. Phillimore. 2016. How reliably can we infer diversity-dependent
505 diversification from phylogenies? *Methods in Ecology and Evolution* 7:1092–1099.
- 506 Etienne, R. S. and J. Rosindell. 2012. Prolonging the past counteracts the pull of the present: protracted
507 speciation can explain observed slowdowns in diversification. *Systematic Biology* 61:204–213.
- 508 Foote, M., R. A. Cooper, J. S. Crampton, and P. M. Sadler. 2018. Diversity-dependent evolutionary rates
509 in early Palaeozoic zooplankton. *Proceedings of the Royal Society of London B: Biological sciences*
510 285:20180122.
- 511 Foote, M. and A. I. Miller. 2006. *Principles of paleontology*. W.H. Freeman, New York.
- 512 Fraser, C. I., S. C. Banks, and J. M. Waters. 2015. Priority effects can lead to underestimation of
513 dispersal and invasion potential. *Biological Invasions* 17:1–8.
- 514 Gerhold, P., J. F. C. Jr, M. Winter, I. V. Bartish, and A. Prinzing. 2015. Phylogenetic patterns are not
515 proxies of community assembly mechanisms (they are far better). *Functional Ecology* 29:600–614.
- 516 Germain, R. M., J. T. Weir, and G. Benjamin. 2016. Species coexistence: macroevolutionary
517 relationships and the contingency of historical interactions. *Proceedings of the Royal Society B:*
518 *Biological Sciences* 283:20160047.
- 519 Harmon, L. J., C. S. Andreatzi, F. Dbarre, J. Drury, E. E. Goldberg, A. B. Martins, C. J. Melin,
520 A. Narwani, S. L. Nuismer, M. W. Pennell, S. M. Rudman, O. Seehausen, D. Silvestro, M. Weber, and
521 B. Matthews. 2019. Detecting the macroevolutionary signal of species interactions. *Journal of*
522 *Evolutionary Biology* 32:769–782.

- 523 Heinicke, M. P., W. E. Duellman, and S. B. Hedges. 2007. Major Caribbean and Central American frog
524 faunas originated by ancient oceanic dispersal. *Proceedings of the National Academy of Sciences*
525 104:10092–10097.
- 526 HilleRisLambers, J., P. B. Adler, W. S. Harpole, J. M. Levine, and M. M. Mayfield. 2012. Rethinking
527 community assembly through the lens of coexistence theory. *Annual Review of Ecology, Evolution, and*
528 *Systematics* 43:227–248.
- 529 Iturralde-Vinent, M. A. 2006. Meso-cenozoic Caribbean paleogeography: Implications for the historical
530 biogeography of the region. *International Geology Review* 48:791–827.
- 531 Jablonski, D. 2008. Biotic interactions and macroevolution: Extensions and mismatches across scales and
532 levels. *Evolution* 62:715–739.
- 533 Janzen, T., S. Höhna, and R. S. Etienne. 2015. Approximate bayesian computation of diversification
534 rates from molecular phylogenies: introducing a new efficient summary statistic, the nltt. *Methods in*
535 *Ecology and Evolution* 6:566–575.
- 536 Jønsson, K. A., P.-H. Fabre, S. A. Fritz, R. S. Etienne, R. E. Ricklefs, T. B. Jørgensen, J. Fjeldså,
537 C. Rahbek, P. G. P. Ericson, F. Woog, E. Pasquet, and M. Irestedt. 2012. Ecological and evolutionary
538 determinants for the adaptive radiation of the Madagascan vangas. *Proceedings of the National*
539 *Academy of Sciences* 109:6620–6625.
- 540 Lambert, A., H. Morlon, and R. S. Etienne. 2014. The reconstructed tree in the lineage-based model of
541 protracted speciation. *Journal of Mathematical Biology* . In press. doi: 10.1007/s00285-014-0767-x.
- 542 Laudanno, G., B. Haegeman, and R. S. Etienne. 2019. Additional analytical support for a new method
543 to compute the likelihood of diversification models. *bioRxiv* .
- 544 Losos, J. B. 2011. Seeing the forest for the trees: The limitations of phylogenies in comparative biology.
545 *The American Naturalist* 177:709–727.
- 546 MacArthur, R. H. and E. O. Wilson. 1967. *Island Biogeography*. Princeton University Press, Princeton,
547 NJ.
- 548 Matzke, N. J. 2013. Probabilistic historical biogeography: new models for founder-event speciation,
549 imperfect detection, and fossils allow improved accuracy and model-testing. *Frontiers of Biogeography*
550 5:242–248.

- 551 Matzke, N. J. 2014. Model Selection in Historical Biogeography Reveals that Founder-Event Speciation
552 Is a Crucial Process in Island Clades. *Systematic Biology* 63:951–970.
- 553 Mayfield, M. M. and J. M. Levine. 2010. Opposing effects of competitive exclusion on the phylogenetic
554 structure of communities. *Ecology Letters* 13:1085–1093.
- 555 Narwani, A., B. Matthews, J. Fox, and P. Venail. 2015. Using phylogenetics in community assembly and
556 ecosystem functioning research. *Functional Ecology* 29:589–591.
- 557 Ojosnegros, S., N. Beerenwinkel, T. Antal, M. A. Nowak, C. Escarmís, and E. Domingo. 2010.
558 Competition-colonization dynamics in an rna virus. *Proceedings of the National Academy of Sciences*
559 107:2108–2112.
- 560 Phillimore, A. B. and T. D. Price. 2008. Density-dependent cladogenesis in birds. *PLoS Biology*
561 6:0483–0489.
- 562 Pigot, A. L. and R. S. Etienne. 2015. A new dynamic null model for phylogenetic community structure.
563 *Ecology Letters* 18:153–163.
- 564 Pires, M. M., D. Silvestro, and T. B. Quental. 2017. Interactions within and between clades shaped the
565 diversification of terrestrial carnivores. *Evolution* 71:1855–1864.
- 566 Proches, S., J. R. U. Wilson, D. M. Richardson, and M. Rejmnek. 2008. Searching for phylogenetic
567 pattern in biological invasions. *Global Ecology and Biogeography* 17:5–10.
- 568 Rabosky, D. L. 2013. Diversity-dependence, ecological speciation, and the role of competition in
569 macroevolution. *Annual Review of Ecology, Evolution, and Systematics* 44:481–502.
- 570 Rabosky, D. L. and R. E. Glor. 2010. Equilibrium speciation dynamics in a model adaptive radiation of
571 island lizards. *Proceedings of the National Academy of Sciences* 107:22178–22183.
- 572 Rabosky, D. L. and A. H. Hurlbert. 2015. Species richness at continental scales is dominated by
573 ecological limits. *The American Naturalist* 185:572–583.
- 574 Rabosky, D. L. and I. J. Lovette. 2008. Density-dependent diversification in North American wood
575 warblers. *Proceedings of the Royal Society of London B* 275:2363–2371.
- 576 Raup, D. M., S. J. Gould, T. J. M. Schopf, and D. S. Simberloff. 1973. Stochastic models of phylogeny
577 and the evolution of diversity. *Journal of Geology* 81:525–542.

- 578 Revell, L. J. 2012. phytools: an R package for phylogenetic comparative biology (and other things).
579 *Methods in Ecology and Evolution* 3:217–223.
- 580 Richter, F., B. Haegeman, R. S. Etienne, and E. C. Wit. 2020. Introducing a general class of species
581 diversification models for phylogenetic trees. *Statistica Neerlandica* 74:261–274.
- 582 Schenk, J. J., K. C. Rowe, and S. J. Steppan. 2013. Ecological Opportunity and Incumbency in the
583 Diversification of Repeated Continental Colonizations by Muroid Rodents. *Systematic Biology*
584 62:837–864.
- 585 Sepkoski, J. 1996. Competition in macroevolution: the double wedge revisited. Pages 211–255 *in*
586 *Evolutionary Paleobiology* (J. L. D. Jablosinski, D.H. Erwin, ed.). University of Chicago Press.
- 587 Silvertown, J. 2004. The ghost of competition past in the phylogeny of island endemic plants. *Journal of*
588 *Ecology* 92:168–173.
- 589 Silvestro, D., A. Antonelli, N. Salamin, and T. B. Quental. 2015. The role of clade competition in the
590 diversification of North American canids. *Proceedings of the National Academy of Sciences*
591 112:8684–8689.
- 592 Stanley, S. M. 1973. An explanation for cope’s rule. *Evolution* 27:1–26.
- 593 Valente, L., R. S. Etienne, and L. M. Dávalos. 2017a. Recent extinctions disturb path to equilibrium
594 diversity in Caribbean bats. *Nature Ecology & Evolution* 1:0026.
- 595 Valente, L., R. S. Etienne, and J. C. Garcia-R. 2019. Deep macroevolutionary impact of humans on New
596 Zealand’s unique avifauna. *Current Biology* 29:2563–2569.e4.
- 597 Valente, L., J. C. Illera, K. Havenstein, T. Pallien, R. S. Etienne, and R. Tiedemann. 2017b. Equilibrium
598 bird species diversity in Atlantic islands. *Current Biology* 27:1660–1666.e5.
- 599 Valente, L. M., R. S. Etienne, and A. B. Phillimore. 2014. The effects of island ontogeny on species
600 diversity and phylogeny. *Proceedings of the Royal Society B: Biological Sciences* 281:20133227.
- 601 Valente, L. M., A. B. Phillimore, and R. S. Etienne. 2015. Equilibrium and non-equilibrium dynamics
602 simultaneously operate in the Galápagos islands. *Ecology Letters* 18:844–852.
- 603 Valkenburgh, B. V. 1999. Major patterns in the history of carnivorous mammals. *Annual Review of*
604 *Earth and Planetary Sciences* 27:463–493.

- 605 Violle, C., D. R. Nemergut, Z. Pu, and L. Jiang. 2011. Phylogenetic limiting similarity and competitive
606 exclusion. *Ecology Letters* 14:782–787.
- 607 Walker, T. D. and J. W. Valentine. 1984. Equilibrium models of evolutionary species diversity and the
608 number of empty niches. *American Naturalist* 124:887–899.
- 609 Whittaker, R. J., K. A. Triantis, and R. J. Ladle. 2008. A general dynamic theory of oceanic island
610 biogeography. *Journal of Biogeography* 35:977–994.
- 611 Wilcox, T. M., M. K. Schwartz, and W. H. Lowe. 2018. Evolutionary community ecology: Time to think
612 outside the (taxonomic) box. *Trends in Ecology & Evolution* 33:240 – 250.