

Supplemental Text. Estimating diversification rates from Amazon plant phylogenies.**1. Temperature variations through time**

For the environment-dependent diversification analyses, we used the global surface temperature curve as presented in Boschman and Condamine (2022), which captures major trends in global climate through time. This curve is computed from $\delta^{18}\text{O}$ data measured from deep-sea benthic foraminifera shells preserved in oceanic sediments derived from datasets by Westerhold et al. (2020) for the Cenozoic (66-0 Ma), and from Veizer and Prokoph (2015) for the Cretaceous (80-66 Ma). The $\delta^{18}\text{O}$ data was converted into absolute temperature values using the equations of Hansen et al. (2013), which convert $\delta^{18}\text{O}$ to deep-ocean temperatures (T_{do}) and subsequently, to surface temperatures (T_s). We summarized these data into a continuous estimate of temperature through time using a smoothing spline (degrees of freedom: 80), thereby smoothening geographical variations (Veizer and Prokoph 2015). As a result, the curve reflects global-scale temperature trends that can be expected to have led to temporally coordinated diversification changes in several clades rather than local or seasonal fluctuations (Mayhew et al. 2012; Condamine et al. 2019; Boschman and Condamine 2022). The Amazon (i.e. South American continent) did not move significantly in latitude throughout the Neogene (see Fig. 1), meaning that average global temperature trends do not have to be corrected for plate tectonic motion.

2. Andean uplift through time

For a curve of Andean uplift, we used the curve for the North-Central Andes computed by Boschman and Condamine (2022), which in turn is based on the reconstruction of paleoelevation in the Andes since 80 Ma of Boschman (2021). Boschman and Condamine (2022) converted this reconstruction into uplift curves (in m.a.s.l. through geological time) for seven individual geomorphological domains that can be used in birth-death analyses. Here, we use their curve for elevation through time for the northern and north-central Andes (domains 1-3; see Figures 1 and 2 in Boschman and Condamine (2022)).

3. Modeling the effects of environmental change on diversification of Amazonian clades

Here we use the environment-dependent diversification modeling approach developed by Condamine et al. (2013, 2019), implemented in the R-package *RPANDA* (Morlon et al. 2016). We fitted 14 diversification models to each of the eight selected phylogenies using maximum likelihood (Stadler 2013; Morlon 2014). We consider four types of models with diversification rates that are constant (2 models), time-varying (4 models), temperature-dependent (4 models), and elevation-dependent (4 models; Table 1). These models are fitted by maximum likelihood using the *fit_bd* (for the time-constant and time-varying models) and *fit_env* functions (for the temperature- and elevation-dependent models) from the R-package *RPANDA* 1.9 (Morlon et al. 2016). We consider phylogenies of n species sampled from the present, and allow for the possibility that extant species are not included in the sample by assuming that each extant species was sampled with probability $f \leq 1$. We accounted for missing species by specifying the sampling fraction corresponding to each phylogeny. We used the “crown” condition, which conditions the likelihood of a speciation event at the crown age and survival of the two daughter lineages.

Table 1. Descriptions of the 14 different birth-death models fitted to the eight Amazonian plant clades, including speciation and extinction equations, the number of free parameters to optimize by maximum likelihood, and the model acronym.

Type of model	Model description	Model equation	Number of parameters	Model acronym
Constant-rate models	Constant speciation and no extinction	$\lambda(t)=\lambda_0$ and $\mu(t)=0$	1	BCST
	Constant speciation and constant extinction	$\lambda(t)=\lambda_0$ and $\mu(t)=\mu_0$	2	BCSTDCST
Time-dependent models	Speciation variable and no extinction	$\lambda(t)=\lambda_0e^{\alpha t}$ and $\mu(t)=0$	2	BTimeVar
	Speciation variable and constant extinction	$\lambda(t)=\lambda_0e^{\alpha t}$ and $\mu(t)=\mu_0$	3	BTimeVarDCST
	Constant speciation and extinction variable	$\lambda(t)=\lambda_0$ and $\mu(t)=\mu_0e^{\beta t}$	3	BCSTDTimeVar
	Both speciation and extinction variable	$\lambda(t)=\lambda_0e^{\alpha t}$ and $\mu(t)=\mu_0e^{\beta t}$	4	BTimeVarDTimeVar
Temperature-dependent models	Speciation variable and no extinction	$\lambda(t)=\lambda_0e^{\alpha T(t)}$ and $\mu(t)=0$	2	BTempVar
	Speciation variable and constant extinction	$\lambda(t)=\lambda_0e^{\alpha T(t)}$ and $\mu(t)=\mu_0$	3	BTempVarDCST
	Constant speciation and extinction variable	$\lambda(t)=\lambda_0$ and $\mu(t)=\mu_0e^{\beta T(t)}$	3	BCSTDTempVar
	Both speciation and extinction variable	$\lambda(t)=\lambda_0e^{\alpha T(t)}$ and $\mu(t)=\mu_0e^{\beta T(t)}$	4	BTempVarDTempVar
Elevation-dependent models	Speciation variable and no extinction	$\lambda(t)=\lambda_0e^{\alpha A(t)}$ and $\mu(t)=0$	2	BAndesVar
	Speciation variable and constant extinction	$\lambda(t)=\lambda_0e^{\alpha A(t)}$ and $\mu(t)=\mu_0$	3	BAndesVarDCST
	Constant speciation and extinction variable	$\lambda(t)=\lambda_0$ and $\mu(t)=\mu_0e^{\beta A(t)}$	3	BCSTDAndesVar
	Both speciation and extinction variable	$\lambda(t)=\lambda_0e^{\alpha A(t)}$ and $\mu(t)=\mu_0e^{\beta A(t)}$	4	BAndesVarDAndesVar

In the time-dependent models, λ or both λ and μ vary as a continuous function of time (Table 1): $\lambda(t)=\lambda_0e^{\alpha t}$ or $\mu(t)=\mu_0e^{\beta t}$, where λ_0 (μ_0) is the speciation (extinction) rate at present. A positive α (β) reflects a slowdown of speciation (extinction) towards the present, while a negative α (β) reflects a speed-up of speciation (extinction) towards the present, and the sign and value of α and β depends on the data and model optimization. In the environment-dependent models, speciation rates, extinction rates, or both vary as a continuous function of Andean elevation A or temperature T , for which the curves are computed using a spline interpolation which the degree of freedom set to 80 ($df=80$ in the *fit_env* function). We consider the same exponential dependency as above, but with t replaced by $T(t)$ or $A(t)$. In this case λ_0 (μ_0) is the expected speciation (extinction) rate under a temperature of 0°C or an altitude of 0 meter, and α (β) measures the sign and strength of the temperature or paleoelevation dependence. A positive α (β) indicates that speciation (extinction) rates are higher under warm climatic conditions or when elevations were high, while a negative α (β) indicates that speciation (extinction) rates are higher under cold climatic conditions or when elevations were low.

We fitted each of the models to each phylogeny by maximum likelihood, starting with the simplest (constant rate) models and progressively increasing in complexity. The maximum-likelihood algorithm optimizes parameter values (of λ_0 , μ_0 , α and/or β) that maximize the probability of the observed data (the phylogenetic tree) under a given model. Because these optimization algorithms can be sensitive to the choice of initial parameter values (they can converge to local optima in the vicinity of the initial parameter values), we informed the initial parameter values of more complex models by those previously estimated on simpler models. The 14 tested models are not all nested, and we used the corrected Akaike Information Criterion (AICc; Burnham and Anderson 2002) to compare models. The AICc is

useful to compare the probability of observing branching times as explained by various individual paleoenvironmental variables (Condamine et al. 2015, 2018, 2019). A series of models can be designed to quantify the effect that various environmental variables, taken in isolation, had on diversification. We thus compared the AICc scores for the best-fit models between multiple environmental variables (temperature, Andean uplift) to determine which has the strongest effect on diversification. The best-fitting model is selected using the lowest AICc score but we also report the second-best model.

References

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