

Supporting Information

Guilhaumon *et al.* 10.1073/pnas.0803610105

SI Materials and Methods

Information Theoretical Analysis of SARs. Over the last decade, statistical science has been moving away from the classical Null Hypotheses Testing (NHT, refs. 1, 2) framework. In the present study, nonnested SAR models are subject to selection which raises methodological issues: hypothesis testing is problematic in this context, and the use of classical tools such as the adjusted coefficient of multiple determination (R_a^2) is not advocated as it has no strong theoretical justification (3). The information-theoretic framework for model-selection departs from the NHT paradigm as it is based on the evaluation of multiple working hypotheses. This evaluation of concurring hypotheses each represented by a different model is achieved through the estimation of Kullback-Leibler (K-L) information (or distance, ref. 4):

$$I(f,g) = \int f(x) \log\left(\frac{f(x)}{g(x|\theta)}\right) dx \quad [1]$$

is the “information” lost when the model g (with parameters θ) is used as an approximation of the full reality or truth f . Similarly, $I(f,g)$ is interpreted as the distance from the approximating model to full reality (5). The principle of information theoretical model selection is to find within a predefined set of models the one that minimizes $I(f,g)$. However, because it requires knowledge both of full reality and the parameters for each candidate model, the calculation of the K-L distance remains intractable. Akaike (6) developed a method to approximate $I(f,g)$ based on the empirical log-likelihood function: the Akaike Information Criterion (AIC):

$$AIC = -2\log(L(y|\hat{\theta})) + 2p \quad [2]$$

where $\hat{\theta}$ is the maximum likelihood estimate of the vector of parameters, $L(y|\hat{\theta})$ is the logarithm of the likelihood of the data evaluated at $\theta = \hat{\theta}$, and p is the number of estimated parameters in the model (which includes the estimated variance).

Although AIC constitutes the foundation of the information-theoretic model selection framework, it may perform poorly when the sample size n is small (more precisely when $n/P < 40$, ref. 5). To account for this potential source of bias, Sugiura (7) derived the corrected Akaike’s information criterion (AICc):

$$AICc = AIC + \frac{2p(p+1)}{n-p-1} \quad [3]$$

Equivalently, in the context of nonlinear regression (under assumption of normality of residuals and homoscedasticity, ref. 5):

$$AICc = n \log\left(\frac{RSS}{n}\right) + 2np \frac{n}{n-np-1} \quad [4]$$

where RSS is the residual sum of squares.

Information-theoretic Criteria (IC such as AIC and AICc) are built such that the first term, representing the lack of fit of the model to the observed data, is penalized by the second term, which captures model complexity. The lower the IC associated with a model, the better this model is considered in explaining the data. In the present study, we used AIC or AICc when appropriate. Because AIC and AICc produce relative measures, absolute values are not relevant to compare models and the

selection is usually based on Akaike weights. For a fitted model i , its weight w_i is given by:

$$w_i = \frac{e^{-1/2\Delta_i}}{\sum_{r=1}^M e^{-1/2\Delta_r}} \quad [5]$$

where M is the number of models in the set and Δ_i is defined as $\Delta_i = IC_i - IC_{\min}$ with IC_{\min} the IC value for the best model. Akaike’s weights are interpreted in terms of probabilities of a given model being the best in explaining the data within a predefined set of alternative models. When the data support more than a single model (i.e., no w_i is higher than 0.9; ref. 5), robust inferences can be carried out by averaging inferences within the set of models with respect to their w_i . As advocated for non-nested models, we obtained multimodel SARs by averaging the model predictions with respect to their weight:

$$\bar{S} = \sum_{i=1}^M \hat{S}_i w_i \quad [6]$$

where \bar{S} is the multimodel averaged species richness and \hat{S}_i is the vector of species richness inferred from model i .

Confidence Intervals and Ecoregion Ranking. The biological richness (generally expressed as the number of species, of endemic species or of threatened species) of regions with varying size should be compared by controlling for the effect of area. Since the beginning of the study of the SAR, richness has been recognized to increase with area at a decreasing rate (8). Thus, to control for the effect of area, the use of species-area ratios (e.g., ref. 9) has been found to be problematic (10, 11) as this method implicitly assumes a linear relationship between richness and area and thus produces over-estimated relative diversity for the smallest areas (12). Indeed, accounting for the non-linearity of the SAR through the use of a log-linear power SAR rescaling (a linear relationship is assumed between the logarithm of richness and the logarithm of area) dramatically changes the ranking of regions with respect to their biological richness. Furthermore, this prioritization scales in better agreement with previous studies and knowledge of global biodiversity patterns (10, 11). Although the power model is generally assumed, it may not hold at all scales (13) and its use may not be ubiquitously appropriate (14–16). Moreover, it has been shown that the choice of the SAR model affects the identification of hotspots (17–19). Consequently, one step further in the rescaling of biological richness with respect to area is the incorporation of the uncertainty about the best fitting SAR model (17, 18).

The detection of biodiversity hotspots by SARs is achieved by ranking regions with respect to their displacement above the regression line (17–20). How to quantify the displacement above the SAR is still controversial. The residuals of the SAR have been used repeatedly (17–20) but fail to provide a formal criterion for when to select a region as being a hotspot (21). The use of the 95% confidence limits of the intercept of the log-linear power SAR (21) is also problematic as it relies on the assumption that the dataset could adequately be described by a linearized power SAR.

Devising a ranking methodology robust to the processes that underlie species-area patterns we compared the regions with

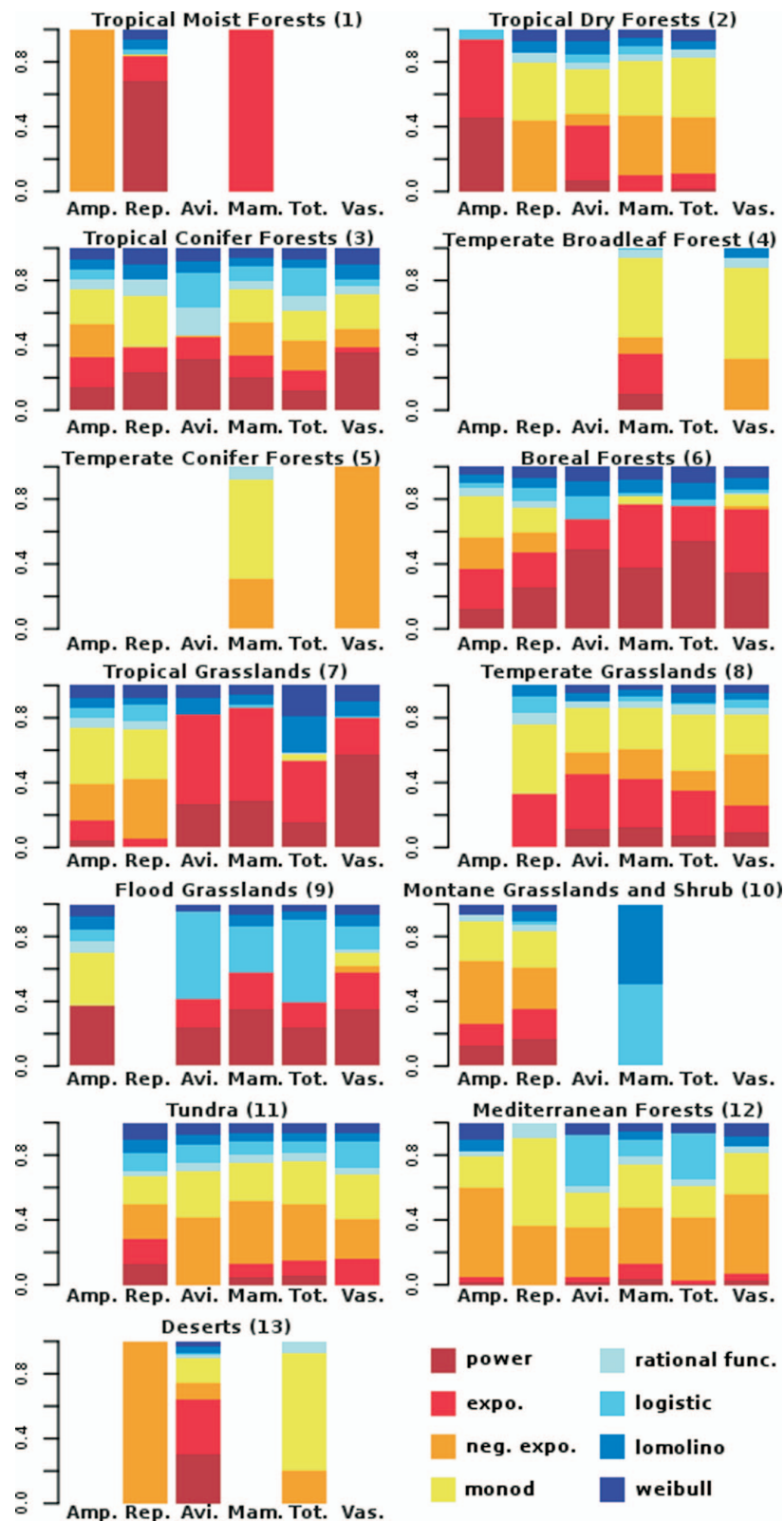


Fig. S1. SAR model selection patterns for the BIC analysis. Patterns of model selection are presented in each biome for amphibians (Amp.), reptiles (Rep.), birds (Avi.), mammals (Mam.), total vertebrates (Tot.), and vascular plants (Vas.). The height of each fraction of the colored band is proportional to the probability (Akaike weight) that each model [see color legend, exponential (expo.), negative exponential (neg. expo.), rational function (rational func.)] is the best in explaining the dataset. A lack of colored band means that none of the eight SAR models was statistically valid for the corresponding dataset.

Table S2. Forms of SAR used in the study

Name	Formula	Number of parameters	Shape	Asymptotic nature
Power	$S = cA^z$	2	Convex	No
Exponential	$S = c + z \log(A)$	2	Convex	No
Negative exponential	$S = c(1 - \exp(-zA))$	2	Convex	Yes
Monod	$S = (cA) / (z + A)$	2	Convex	Yes
Rational function	$S = (c + zA) / (1 + fA)$	3	Sigmoid	Yes
Logistic	$S = c / (1 + \exp(-zA + f))$	3	Sigmoid	Yes
Lomolino	$S = c / (1 + (z^{\log(f/A)})$	3	Sigmoid	Yes
Cumulative Weibull	$S = c(1 - \exp(-zA^f))$	3	Sigmoid	Yes

Table S3. R^2 values for multimodel inferences

	Biomes													Means
	1	2	3	4	5	6	7	8	9	10	11	12	13	
Amp	0.17	0.02	0.36	-	-	0.34	0.3	-	0.11	0.06	-	0.21	-	0.2
Rep	0.3	0.06	0.56	-	-	0.15	0.43	0.1	-	0.04	0.25	0.21	0.06	0.22
Avi	-	0.51	0.47	-	-	0.45	0.58	0.44	0.33	-	0.29	0.39	0.1	0.4
Mam	0.46	0.33	0.4	0.45	0.22	0.52	0.38	0.46	0.24	0.02	0.21	0.38	-	0.34
Tot	-	0.45	0.37	-	-	0.49	0.69	0.56	0.42	-	0.23	0.47	0.14	0.42
Vas	-	-	0.69	0.25	0.14	0.47	0.41	0.27	0.23	-	0.26	0.16	-	0.32
Means	0.31	0.27	0.48	0.35	0.18	0.4	0.47	0.37	0.27	0.04	0.25	0.3	0.1	0.32

See Fig. S1 for biomes names and taxa description. Dash cells correspond to biome-taxon datasets that could not be fit by any of the models.

Biome	Higher taxa	power	expo	neg. expo.	Monod	rational func.	logistic	Lomolino	Weibull
11	Tot	0.05	0.084	0.305	0.233	0.064	0.107	0.07	0.086
11	Vas	-	0.133	0.205	0.227	0.062	0.214	0.066	0.093
12	Amp	0.017	0.024	0.486	0.169	0.047	0.001	0.108	0.148
12	Rep	-	-	0.343	0.513	0.144	-	-	-
12	Avi	0.012	0.021	0.228	0.164	0.047	0.427	-	0.101
12	Mam	0.034	0.072	0.285	0.227	0.065	0.162	0.067	0.088
12	Tot	0.007	0.015	0.297	0.15	0.043	0.394	-	0.094
12	Vas	0.027	0.033	0.428	0.22	0.063	0.003	0.097	0.128
13	Amp	-	-	-	-	-	-	-	-
13	Rep	-	-	1	-	-	-	-	-
13	Avi	0.247	0.281	0.081	0.131	0.044	0.038	0.091	0.087
13	Mam	-	-	-	-	-	-	-	-
13	Tot	-	-	0.177	0.616	0.207	-	-	-
13	Vas	-	-	-	-	-	-	-	-

For each biome, values correspond to model weights (w_i) that are equivalent to model probabilities in being the best to fit the dataset (see Fig. S1 for biome names, taxa, and model description). Dash cells correspond to biome-taxon datasets that could not be fit by any of the models.